

Fundamentals of Chinese Reading:  
Exploring a Corpus of Eye Movements in Chinese  
Passage Reading

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## **Declaration**

I have read and understood The University of Edinburgh guidelines on Plagiarism and declare that this written dissertation is all my own work except where I indicate otherwise by proper use of quotes and references.

## **Abstract**

A large corpus of data of natural reading in Chinese was explored using linear mixed effects analyses conducted in R. The effects of word length, word frequency and functorhood on first fixation, first pass gaze duration and skipping rates were examined. Analyses showed a strong effect of word length on durational measures: longer first pass gaze durations were associated with longer words; surprisingly, the reverse was true for first fixation durations. Skipping showed strong effects of both word length and frequency. Results are discussed in conjunction with current theories of eye movements in reading.

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## 1 Introduction

Reading is a highly complex task, which requires the coordination of many levels of visual, cognitive and comprehension processes. Over the last several decades, reading research has covered impressive ground in establishing eye movement characteristics and the factors that influence them.

However, the vast majority of these studies have focused on English and other alphabetic languages. As an illustration, in his extensive landmark review of two decades of reading research, Rayner (1998) dedicates only a single paragraph to the findings from reading in Chinese and Japanese, and then only with reference to the perceptual span. Consequently, relatively little is known about eye movement patterns in radically different orthographies, such as Chinese. It should be emphasised that the importance of investigating Chinese reading lies not only in understanding the language-specific reading processes of a language read by a large proportion of the world's population; uncovering similarities and differences in reading the different types of script also helps establish which of the *known* eye movement patterns reflect universal processes involved in reading and which are peculiar to the characteristics of the particular orthography under study (i.e. alphabetic writing systems). Establishing which characteristics occur universally across languages and which are script- or language-specific will in turn inform the general model of reading.

Though the field of reading is young with respect to Chinese, during the past decade a number of studies have investigated basic eye movement characteristics in Chinese (e.g. Chen, Song, Lau, Wong and Tang, 2003; Chen & Tang, 1998; Feng, 2006; Inhoff & Liu, 1998; Liu, Inhoff, Ye, & Wu, 2002; Tsai, Lee, Lin, Tzeng, & Hung, 2006; Tsai, Lee, Tzeng, Hung, & Yen, 2004; Sun, Morita & Stark, 1985; Yan, Tian, Bai, & Rayner, 2006; Yang & McConkie, 1999; Yen, Tsai, Tzeng, & Hung, 2008). However, the focus of most of studies of has been either single word recognition or sentence reading, with relatively little attention paid to the reading of longer passages. The present study explores the eye movement patterns involved in reading this logographic script in the arguably more natural

task of reading passages.

## **1.2 Purpose of the present study**

As a result of the dominance of alphabetic languages in eye tracking research to date, relatively little is known about the eye movement characteristics of reading in languages with radically different orthographies. The central aim of this study, therefore, is to investigate some of the basic eye movement patterns involved reading Chinese and contribute to an understanding of how readers of Chinese move their eyes across text during reading. In conjunction with previous findings from other languages, we hope this will in turn cast light on the interplay of language-specific and orthographic effects on the one hand, and on the other, the universal processes involved in extracting information from text in reading.

An important aspect of the present study is its use of a database of passages of natural text. Although an emerging interest in Chinese reading has produced a number of studies in Chinese in recent years, most of these have so far concentrated on either individual word recognition or single sentence reading. Therefore, a particular aim of the present study is to examine eye movement patterns as readers of Chinese take part in natural reading. Ecological validity is maintained by using real-world extracts from news articles, presented in paragraphs spanning several lines. This allows the study to present analyses of eye movement characteristics that, to a large extent, match natural reading conditions.

## 2 Theoretical Background

### 2.1 Eye movements as a window on cognitive processing: the visuomotor system in reading

The characteristic movements of the eyes during reading have been investigated extensively as indicators of the underlying moment-by-moment visual and cognitive processing involved in comprehending written text (e.g. Just & Carpenter, 1983; Starr & Rayner, 2001). Although, intuitively, it may seem as if the eyes glide smoothly across the page, in fact this is not the case. Rather, there is an alternation between two main phases. During reading, the eyes continually make rapid movements, called *saccades*. These are interspersed with *fixations*, periods when the eyes remain relatively still, which tend to last around 200-300 ms (Rayner, 1998). No new information is extracted during saccades, because of the high speed of eye movement, which can be as fast as 500 degrees per second (Uttal & Smith, 1968). The reduction of sensitivity to visual input during these rapid movements is called *saccadic suppression*, and prevents input that would otherwise be perceived as a blur (Matin, 1974).

During fixations, perception is limited to a small area of the visual field, called the *perceptual span*, and saccades are made in order to bring new words into this high-acuity area of vision. The ability to extract information from the perceptual span is 'attentional' in that it varies depending on where attention is directed. Presumably, this is because there is a shift in visuospatial attention from the currently fixated word toward the next fixation target before there is any movement of the eyes. The size and shape of the perceptual span develops with age and reading experience, and varies with text difficulty (Inhoff, Pollatsek, Posner & Rayner, 1989; Rayner, 1986). As readers become more skilled, attention is habitually focused in the direction of forthcoming text. One result of this is that the effective field of vision is skewed in the direction of reading, so in both Chinese and English it stretches further to the right of fixation than to the left. In left-to-right languages, such as Hebrew (Pollatsek, Bolozky, Well, & Rayner, 1981) and Arabic (Rabia & Siegel, 1995), it is skewed to the left. Interestingly, not only the direction, but also the actual size of the perceptual

span seems to be language-dependant (see Calvo & Meseguer, 2002; Kliegl, Grabner, Rolfs, & Engbert, 2004, for recent discussions).

The perceptual span can be further divided into areas corresponding to the fovea and parafovea. With normal text size and viewing distance, the fovea generally subtends approximately 2 degrees of visual angle, or 7-8 letters in English, and is equally distributed on either side of the point of fixation, although information available to the left of fixation is generally limited to the currently fixated word (Clifton, Staub & Rayner, 2007). The foveal region is where visual acuity is highest. Outside the fovea, there is a sharp decline in acuity, although words can generally be identified up to 8 letters to the right of the current fixation (Rayner, Well, Pollatsek & Bertera, 1982). However, some low-level visual information, such as spaces marking word boundaries, can also be obtained from the parafovea. Readers of English can generally detect useful information around 14-15 letter spaces to the right of fixation, and, within the current word, up to about 2-3 letters to the left.

Intuitively, one might assume that the ability to extract information from text relies predominantly on low-level factors pertaining to the mechanics of the visual system, such as what distance from the current location the eyes are able to bring a word into focus. However, constraints of both visual acuity and processing resources are implicated in the size and shape of the perceptual span. Importantly, as with the size and shape of the effective field of vision, the *type* of information that can be extracted during parafoveal preview is also limited and language-dependant (Pynte & Kennedy, 2006, Yen et al., 2008, Yen et al, 2009).

Saccade planning requires two important types of decision: *when* to end the current fixation and move the eyes to a new location, and *where* to send the eyes. A growing body of evidence suggests that these two aspects of eye movement planning are controlled by two overlapping but separable neural pathways (Findlay & Walker, 1999). Some evidence for this comes from nonreading studies of oculomotor control. For example, Fischer, Biscaldi and Gezeck (1997) found that age was correlated with voluntary control of initiating saccades and inhibition of inappropriate responses, but there was no age correlation for



maintaining fixations. In reading, although voluntary control may be involved to some extent in deciding fixation durations, it is largely associated with spatial movement (ie the *where* decision), such as selecting the location of the next target (Feng, Miller, Shu & Zhang, 2009).

Because saccades are motor movements, they take time to plan and execute (Rayner, 1998). This is known as *saccade latency*. Based on studies of reading of alphabetic languages, it has traditionally been assumed that the spatial, visuomotor decision of where to direct the next saccade relies on very basic, low-level visual information. The decision about where to send the eyes is made very quickly, usually in less than 200ms (Rayner, 1998). Therefore, skilled saccade planning is thought to reflect not only expertise in the process of reading, but also the mechanics of the eye and visual system itself. For example, even excluding the time taken to decide specifically when and where to move the eyes, planning the movement itself takes at least 150-175 ms (Abrams & Jonides, 1988; Rayner, Slowiaczek, Clifton, & Bertera, 1983; Salthouse & Ellis, 1980). In silent reading, mean fixation durations are usually around 200-250 ms (Rayner, 1998). This relatively small difference in fixation times compared with motor planning suggests that saccades are programmed in parallel with comprehension processes.

## **2.2 Eye movement measures**

For the purpose of analysing reading behaviour, the characteristics of eye movement patterns are often broken down into two types of 'decisions' readers make when reading: *when* to move their eyes and *where* to send them (Findlay & Walker, 1999; Fischer, et al., 1997; Rayner, 1998). Studies that have examined saccade movement have established a dichotomy in the factors that affect these two aspects of reading behaviour. The length of time spent looking at a word (i.e., the *when* decision) is primarily determined by the processing difficulty associated with that word (Dreighe, Rayner & Pollatsek, 2005). For example, word frequency, word predictability, neighbourhood size and age of acquisition have all been shown to influence the time spent fixating a word (Altarriba, Kroll, Sholl, & Rayner, 1996; Ashby, Rayner, & Clifton, 2005; Balota, Pollatsek, &

Rayner, 1985; Brysbaert & Vitu, 1998; Calvo & Meseguer, 2002; Drieghe, Brysbaert, Desmet, & De Baecke, 2004; Frisson, Rayner, & Pickering, 2005; Henderson & Ferreira, 1990, 1993; Inhoff & Rayner, 1986; Kennison & Clifton, 1995; Kliegl et al., 2006; Kliegl, Grabner, Rolfs, & Engbert, 2004; McConkie, Kerr, Reddix, & Zola, 1988; Raney & Rayner, 1995; Rayner, 1998; Rayner & McConkie, 1976; Rayner, 1977; Rayner & Duffy, 1986; Rayner, Fischer, & Pollatsek, 1998).

Based on this evidence, it has been argued that the linguistic properties of words play the greatest role in deciding when to move the eyes. The *where* decision, in contrast, is thought to be determined mainly by low-level visual factors, such as word length and inter-word spacing, which have been shown to affect saccade length and landing position within a word (Rayner, Fischer & Pollatsek, 1998). For example, most saccades land slightly left of centre in each word; this is known as the 'preferred viewing position' (Rayner, 1979).

It has also been shown that fixation location is related to processing time. Studies of word recognition in English and alphabetic languages have found that word identification occurs most quickly when fixations are near the centre of the word (Brysbaert & Vitu, 1998; O'Regan, 1990). This is known as the Optimal Viewing Position (OVP) effect. Investigation of the OVP effect in sentence reading led to the discovery of the Inverted Optimal View Position (IOVP) effect. In contrast to word recognition, fixation durations in reading text were longest near the centre of the word. It is unclear why this is the case. Henderson and Ferreira (1990; 1993) suggest that since the centre of the word is optimal for processing, the eyes stay for longer in order to process more information.

### ***Skipping***

Brysbaert and Vitu (1998) reviewed evidence from several studies of eye movement patterns in an attempt to explain the finding that more than one third of words are initially skipped in reading. Word length and launch site (Kerr, 1992) were found to have among the strongest effects on skipping rates. In English, up to 75% of 2-3 letter words are skipped, while 8-letter words are

almost never skipped (Rayner & McConkie, 1976). A word's frequency has a smaller, but significant effect on the likelihood that it is skipped during reading.

### ***Fixation durations***

In both Chinese and English, the proportion of long fixations is greater in younger readers than in skilled readers. Yang and McConkie (2001) suggest that while shorter fixations occur as a sort of default determined by an interaction between fixation and movement mechanisms, longer fixations are the result of interference from higher cognitive processes which alter the interaction between the two centres. This extension of fixation duration might occur, for example, due to comprehension difficulties. This theory assumes that the greater number of long fixations among younger readers occurs as a result of more frequent cognitive intervention triggered by processing difficulty. Presumably, if this proposed cognitive control mechanism is correct, it is universal across languages, and the similar fixation duration patterns could be expected across different languages.

Inhoff (1984) found a dichotomy in the factors that influenced first fixation and pass gaze duration, respectively. In his results, the duration of both the initial fixation and first pass gaze were influenced by word frequency. Only gaze duration, however, was affected by the predictability of the word in context. Based on these results, he proposed that the measure of first fixation duration relates to lexical access, while gaze included processes involved in integration with semantic and contextual information.

## **2.3 Chinese orthography and morphophonetics**

There are several differences that might potentially affect the cognitive processes developed for and applied to the task of reading (Feng et al., 2009). Given that most of what we know about reading comes from studies of English,

and most of the rest comes from other alphabetic languages, it is important to consider what effects the particular orthography of these languages has had on the reading processes that have been established in the reading literature. There are several distinct differences between the Chinese and English writing systems which have potential to impact on eye movements in reading. Three of the major differences are: the basic linguistic unit represented in the script; text density and word length statistics; and finally, the marking of boundaries between linguistic units. The combination of these factors leads to important differences in what information is available to readers of the different orthographies, and when.

Chinese text is made up of evenly spaced strings of box-shaped characters, all of equal width. Although it was historically written vertically, Chinese is now most commonly written horizontally from left to right across the page. Words are made up of one or more characters, with average word length approximately 1.5 characters in text (Feng, 2006; Sun, et al., 1985). According to Academia Sinica Taiwan (1998), a Chinese word corpus containing 54,393 words, the proportion of one-, two-, three- and four-character word entries (token types) is 9.5%, 65.5%, 12.4% and 11.6%, respectively. Based on the same corpus, it is estimated that the proportion of words encountered in text will be 53.8% single-character words and 42.2% will be two-character words (Yen, et al., 2008). These two types of frequency count are known as *token frequency* and *printed frequency*, respectively. The sizable differences in these two sets of frequency counts, particularly with respect to single-character words, reflects the high frequency of a relatively small number of short, one-character words. Alphabetic languages, such as English, use a system of letters, which roughly correspond to phonemes in the spoken language, although there are many exceptions to this general rule. In Chinese, on the other hand, except in very few cases, each character represents a morpheme and corresponds to one spoken syllable. Characters cannot be broken down into smaller units of sound.

An aspect of the Chinese writing system that has been the focus of several recent eye movement studies is in the marking of unit boundaries. In English, spacing is irregular and corresponds to word boundaries. Presumably, this aids in the

parsing of letter strings into words, making features such as word length information available and highly visible in the parafovea, although there has been some debate over this assumption. For example, Epelboim, Booth and Steinman (1993) found that removing inter-word spacing had relatively little effect on eye movement measures in English; small increases in fixation durations were observed and reductions in saccade extent were proportional to the increase in text density. However, in a subsequent analysis, Rayner and Pollatsek (1996) found much larger effects on durational measures (30% slower, on average). In a later study, Rayner, Reichle and Pollatsek (1998) demonstrated effects on the spatial measure of saccade targeting as a result of removing spaces. In their data, landing position of the initial fixation shifted closer to the beginning of the word. Of course, these studies were conducted in English; different reading strategies, and orthographic and linguistic factors are likely to be involved for Chinese. However, despite the discrepancies in these results, it is interesting to note that the landing position distributions in all of these studies preserved a word-based pattern.

From another point of view, comparison with Chinese serves to highlight one aspect where there is a lack of transparency in English. While orthography is an obvious difference between Chinese and English reading, the importance of the differential representation of the morpheme is a factor that is often overlooked in comparisons of the reading behaviour in the respective languages. Features such as syllable and morpheme boundaries, which are marked in Chinese, are not marked in most alphabetic writing systems. The regular character size and between-character spacing in Chinese provides completely reliable information about syllable and morpheme boundaries, making these features completely predictable. It should be noted that this is not purely a feature of the orthography. It is also related to the fact inherent in Chinese morpho-phonetics, that morphemes generally have a one-to-one correspondence with syllables. This makes retrieving syllable timing, as well as boundaries between meaning units, highly predictable in reading. The fact that readers of English cope fairly well without any clues as to the length or boundaries of either syllables or morphemes also serves as a reminder of the flexibility of skilled readers to adapt

to the requirements of the particular reading form. Proficient readers of English or other alphabetic languages might become accustomed to this feature of the writing system and take this parsing skill for granted.

In Chinese, although syllable and morpheme boundary information is readily available, word boundaries are not. The presence or absence of visually distinct word and morpheme boundaries may have consequences for both perception and conceptualization of linguistic units in the respective languages (Feng, et al., 2009). Indeed, when asked to divide text into words, Chinese native speakers often fail to agree on what constitutes a word and where the boundaries are (Tsai & McConkie, 1998). To speakers of languages like English, words are an extremely salient concept. The notion that speakers might not have clear representation of what is and is not a word might seem surprising. However, the situation is not so different in English if one considers cases such as ‘et cetera’ versus ‘etc.’ or ‘per cent’ versus ‘percent’. It seems reasonable to suppose that, if asked count the number of words in a sentence, speakers would rely heavily on information provided by the spacing. Therefore, they would be likely to analyse ‘per cent’ as two words or ‘percent’ as one, for example, despite the fact that each written form represents the same ‘word’ or *lexeme*. (This is an example of cross-dialectal difference in English spelling, with ‘per cent’ more common in British English and ‘percent’ more commonly used in American English).

There has been an assumption in the literature that, for Chinese, a separate process of parsing character strings into words must occur prior to word identification (e.g. Chang, 1993; Hoosain, 1992; Liu, 1974). However, Tsai and McConkie (1998) point out that this may be a misconception. They suggest that rather than being a prerequisite to the process of identifying words, word segmentation may instead occur as a by-product of word identification. Tsai argues that if it were the case that boundary identification must occur before words could be identified, then slower reading rates would have been observed for Chinese compared with English. In fact, comparable reading rates, measured in words per minute, have been found between the two languages (Sun, Morita, & Stark, 1985; Tsai & McConkie, 1995).

However, if it is the case that comprehension requires building smaller units up into words, then the processing cost for this aspect of reading is likely to be higher in Chinese where there are no visual cues for the word unit. Interestingly, Feng et al. (2009) found that this difference was more obvious during reading acquisition than in experienced readers, suggesting that as Chinese readers become more proficient the time taken to identify word boundaries is reduced.

On the other hand, Chinese readers have the advantage of a linguistic system that ensures regular parcelling of morphemes into single of syllables and characters. It may be that even if a process of segmentation is a necessary prerequisite to word identification, the extra time and processing cost of word segmentation is counterbalanced by quicker identification of morphological and syllabic units. If this is the case, we would expect differential fixation duration measures to be associated with words with less predictable word boundaries.

## **Fixed Effects**

### ***Word Frequency***

The effect of word frequency on fixation times was reported as early as Rayner (1977) and Just and Carpenter (1980). Although word frequency is confounded with word length (high-frequency words are shorter, on average, than low frequency words) experiments that controlled for word length still showed strong frequency effects on both first fixation duration and gaze duration (e.g., Rayner & Duffy, 1986; Inhoff & Rayner, 1986; also, see Rayner, 1998; Reichle et al., 2003 for reviews).

### ***Functorhood***

The question of whether functorhood affects eye movement patterns is still under debate. Around 85% of English content words are fixated, while function words are only fixated around 35% of the time (Carpenter & Just, 1983; Rayner & Duffy, 1988). However, functorhood is confounded with word length, frequency and predictability. In studies in English which controlled for these other factors, the effect of functorhood disappeared (\*).

However, in Chinese, given the lack of inter-word spacing, word structure may play a different role. Readers of Chinese have the intuition that function words, such as the nominal and verbal particles ‘的’ and ‘地’ and prepositions, such as ‘在’ act to ‘guide’ the eyes by somehow breaking up the text. Presumably, if these structural words are highly salient to readers, they could aid in word identification and lexical parsing. With fewer visual clues available to aid in the segmenting of character strings into words, Chinese readers may rely more heavily on these structural particles to guide saccade planning.

In a series of letter detection tasks in Hebrew, Koriat & Greenberg (1994) tested empirically the intuition that structural words are somehow processed differently to content words. Their work followed the findings of Healy and colleagues’ (e.g., Corcoran, 1966; Healy, 1976, 1994; Healy & Drewnowski, 1983; Healy, Oliver, & McNamara, 1987; Proctor & Healy, 1985) that when participants were instructed to search for particular letters in text, they were more likely to miss letters that occurred in short, frequent words like *the*, *in* and *from*. Koriat and Greenberg’s research was motivated by the observation that the *missing-letter effect* had been found predominantly in function words. In Hebrew, text does not usually include vowels, so a sequence of consonants is frequently very ambiguous. In many cases, the same string can occur either as a function word or a content word. In one experiment (Koriat & Greenberg, 1991), participants made more errors searching for letters in function words than when the same letter string formed part of a content word. They argue that the participants’ greater difficulty identifying letters in cases where the word was a functor indicates a different type of processing for the two word classes. If the same is true in reading, we might expect this different kind of processing to manifest in distinct eye movement patterns.

## **2.4 Eye movements in Chinese reading**

In order to establish a context for the present study, a brief outline is provided here of relevant findings from previous eye movement studies in Chinese. Where appropriate these are presented with reference to equivalent findings in English



or other languages.

In light of the major differences in appearance and structure of the two types of orthography described above, one might expect this to manifest in distinct eye movement patterns in reading. However, a number of recent studies which have examined the general characteristics of Chinese reading have revealed a surprising number of similarities in reading between the two languages, particularly in measures of duration (Feng, Miller, Shu, & Zhang, 2001; Sun et al., 1985; Tsai & McConkie, 1995, 2003; Yang, 1994; Yang & McConkie, 1994). Firstly, average fixation durations are approximately 225-250 milliseconds in both English (Pollatsek, Rayner, & Collins, 1984) and Chinese (Chen et al., 2003). In a cross-linguistic reading study using comparable English and Chinese texts, Sun and Feng (1999) found very similar results for mean fixation duration (257 ms vs. 265 ms), average saccade length in words (1.71 vs. 1.75 words), and overall reading rate (386 vs. 382 words per minute) for Chinese and English respectively.

Perhaps the clearest differences found in eye movement patterns between the two languages are in the perceptual and saccade spans. Recall that in English, the region of effective vision, or perceptual span, is about 3-4 letters to the left and 14-15 letters to the right, while forward saccades are generally about 7-8 characters in length (Rayner, 1998). Using the self-paced moving window technique, Chen and Tang (1998) measured the viewing time of individual Chinese characters while varying the amount of information visible either side of the character. They found that reading speed was increased when information was available up to two characters to the right. Extending the amount of available information beyond two characters made no difference to reading speed. Further investigation in Chinese, the perceptual span extends about 1 character to the left and 2-3 characters to the right (Chen & Tang, 1998; Inhoff & Liu, 1998). Chen, Song, Lau, Wong and Tang (2003) measured forward saccade extent in Chinese sentence reading. They found saccades moved an average of 2.6 characters, a much smaller figure than has been found in English. This smaller saccade size may not be surprising given the compact nature of the Chinese writing system compared with English. However, what is interesting is

that, in Chinese, the perceptual span is much smaller relative to saccade size than it is in English. This means that in English saccades typically extend to around half of the perceptual span, giving rise to a large amount of overlap of effective visual field in successive saccades. In contrast, saccades in Chinese reading reach almost the end of the perceptual span.

## **2.4 Passage reading and task effects**

Even relatively early in reading research (e.g. Heller, 1982; Tinker, 1958) it was observed that large variations in eye movements could result from adjustments readers made to the particular reading material and purpose of reading. However, when caught up in fine-grained analyses of variation between conditions researchers may tend to lose sight of the fact that 'reading' is a dynamic and hugely variable activity. The sort of reading required for browsing newspaper headlines or scanning an article for a particular reference is quantitatively different to the kind of 'reading' that happens when absorbed in a novel or studying a textbook.

In Rayner, Sereno and Raney (1996) an investigation was made into how reading behaviour, particularly eye movement patterns, was influenced by strategic control. They found that the reading task affected the strength of the word frequency effect. When participants were instructed to read for comprehension, whether a word was high or low frequency had a large effect on eye movement measures; however, when the task was to find target words in the text, the effect disappeared. This is likely to reflect the depth of processing required by the respective tasks. Radach, Huestegge and Reilly (2008) point out that, since reading for comprehension involves deeper and more elaborate processing, more careful reading strategies tend to be used, compared to simple text searches. This, in turn, leads to an enhanced effect of word frequency.

Within the extensive literature in the field of reading that has developed over the last several decades, there is a broad division that can be drawn between two general areas of focus. It has been noted that two sub-cultures of eye tracking research have emerged in these related but separate fields of study (Stanovich,

2003). Each of the separate groups has had their particular aims and interests, and this has in turn influenced the design, methods and materials used in their respective research. On the one hand, eye tracking has been used in psycholinguistic research focused mainly on investigating particular hypotheses in relation to word and sentence processing; on the other hand, the same general eye-tracking technologies have been used in the development of eye-movement control models, where the interest is in how underlying linguistic and visuomotor mechanisms combine and manifest in observable reading behaviour. The division between these sub-fields of research lies not only in the subject of study, but also in the different methodologies and particular techniques typically used by each of these research groups. In an effort to enable the findings of these related but disparate fields of study to be interpreted in a more integrated framework, Radach et al. (2008) investigated how and to what extent top-down factors might influence eye movement patterns in reading. They examined the effects of task (using comprehension versus verification questions) and format (sentence versus passage reading) on durational measures, spatial-visuomotor effects and local lexical processing during reading.

One of the central findings of their study was that, contrary to expectations, the durational measures gaze and first fixation duration were reduced during passage reading compared to sentence reading. Total viewing time, however, was longer than in sentence reading. This suggests that when reading large bodies of text, readers tend to make a quick first pass over the text, then make more regressions to reread text.

### 3 Predictions

We will present predictions in two parts. Firstly a set of predictions is presented within the general framework of the Lexical Segmentation Hypothesis. This is then followed by a second set of predictions that do not specifically relate to the Lexical Segmentation Hypothesis, but which pertain to the variables investigated. Both sets of predictions are made on the basis of: a) the above findings from reading research in Chinese and other languages; b) characteristics of the Chinese orthography and morphosyntax; and c) passage reading and effects of format of the reading material.

#### *The Lexical Segregation Hypothesis*

As discussed above, in alphabetic languages, words are physically separated from each other by spaces in the text, but this is not the case in Chinese. One of the major goals of Chinese reading research is to determine what, if any, implications this has for eye movement patterns in the different scripts. One possibility is that, since there are no physical cues to word boundaries in Chinese, readers develop a saccade targeting strategy that does not rely on word segmentation being completed prior to fixation. We will call this the *Visuo-Spatial Targeting Hypothesis* (VTH). Indeed, some studies have shown a flat distribution of within-word landing positions in Chinese (Chen, et al., 2003). Tsai (1998) argues that 95% of words can be correctly identified through statistical probabilities, matching input strings to a stored lexicon, and using algorithms to solve any ambiguity. He suggests that processing can be carried out on any string of meaningful units, and that these strings need not necessarily be restricted to words. Therefore, he argues, word segmentation can occur as a by-product of this processing rather than as a prerequisite. However, there are a number of problems with this view. Firstly, as in other languages, word-level effects, such as predictability in text, word frequency and word length, have been found to have a robust influence on eye movement measures in Chinese (Chen, et al., 2003; Feng et al., 2009; Tsai & McConkie, 2003).

Another possibility is that a process of word segmentation occurs during parafoveal preview. We refer to this as the *Lexical Segmentation Hypothesis*.

According to this hypothesis, during foveation of the current word (word  $n$ ), the boundary of the word immediately to the right of fixation ( $n + 1$ ) is identified so that  $n + 1$  can be targeted for processing in the following saccade. Several points make this a more likely model. Firstly, recent studies of preview benefit in Chinese, show parafoveal advantage for semantic information. Semantic preview effects have been elusive in English, and as far as we are aware, have not been found in any other language. It seems reasonable to suppose that these two aspects of Chinese reading - word boundary identification and extraction of semantic information - are related. The finding that semantic information is not extracted in parafoveal view in scripts marked with word boundaries suggests a relatively superficial processing is sufficient for saccade planning. On the other hand, saccade planning in Chinese may require a degree of lexical processing to determine word length information. In other words, the semantic parafoveal benefit and the problem of word segmentation could be explained by a system of parafoveal processing that involves activation of lexical information to establish  $n + 1$  word boundaries.

Further evidence for a word segmentation process comes from word-level effects on eye movement measures. For example, as mentioned above several studies have found high frequency words are identified more quickly than low-frequency words. Moreover, Li, Rayner & Cave (2009) showed that parafoveal identification of four-character strings was more accurate when characters made up a single four-character word than when two two-character words were presented. This suggests that processing focuses on the following word, regardless of its length. Presumably, this word-level processing entails determining the boundary of the parafoveal word.

The Lexical Segregation Hypothesis (LSH) makes a number of predictions about eye movements in Chinese reading, outlined below.

#### *Prediction 1: The Lexical Unit Effect*

Integral to the LSH is the idea that Chinese reading involves word-based processing. If this hypothesis is correct, we would expect to see word-level effects on eye movement behaviour. In particular, word frequency, which has

been shown to affect eye movements in other languages, as well as in Chinese word recognition and sentence reading, is expected to affect the durational and spatial measures. Following studies in other languages, higher frequency words are expected to yield shorter fixations and higher skipping rates than their low-frequency counterparts. Conversely, increases in word length should lead to longer fixations and lower skipping rates.

If, on the other hand, processing is character-based, word-level effects should not have reliable effects on eye movement measures.

### *Prediction 2: The Word Length Effect*

Pynte and Kennedy (2006) showed that readers are sensitive to the word length statistics of their language. According to Yen et al. (2008), based on calculations from Academia Sinica Taiwan (1998) 96% percent of words in text will be either one or two characters long. It is likely that reading strategies in Chinese are influenced by these word length frequencies. Perfetti and Tan (1999) propose that Chinese readers develop a kind of default saccade planning strategy, whereby saccade extent is based a default two-character word length. (In their data, around two thirds of words were two characters.) If this is correct, we might expect longer words to have an extra processing cost. Therefore, word length is expected be a strong predictor of durational measures, particular for words longer than two characters.

### *Prediction 3: Landing position distributions*

As discussed, information about word length can be obtained parafoveally in alphabetic languages. It is assumed that this low-level visual information helps readers plan where to send the next saccade (e.g. Morris, Rayner, & Pollatsek, 1990; Rayner, Sereno, & Raney, 1996). Feng et al. (2009) suggest that the lack of spacing in Chinese may preclude oculomotor strategies that rely on access to word length information in the parafovea, reducing the ability to make word-based landing site decisions. This view is consistent with the VTH, which states that word-based saccade targeting relies on low-level, visual information, such as word spacing. Lacking such information, landing site distributions will not correlate with word boundaries.

In contrast to this view, according to the LSH, since word boundary information is obtained parafoveally by a process of lexical segmentation, word-based saccade targeting can occur. A kind of preferred viewing position is predicted, in that landing position distributions will be dependent on word boundary information. However, the length statistics described above are also expected to play an important role in saccade targeting, with saccades more likely to fall on the first or second character.

#### *Further Predictions for the present study*

##### **Fixation durations**

Fischer et al., (1997) proposed that two neural systems are responsible for the *when* and *where* decisions. Feng et al. (2009) suggest that characteristics of the particular orthography have a greater effect on where readers look; how long they spend looking at a word is relatively stable across languages. It has been proposed that this is a manifestation of robust neurological processes that are not affected by specific features of orthography or by reading strategy. Based on this assumption we expect first fixation duration to fall within the 225-250 ms range found in previous reading studies of English and Chinese.

##### **Skipping**

Feng and colleagues' proposal predicts that cross-linguistic differences will emerge in spatial measures. With respect to skipping rates, however, many studies have found comparable rates between Chinese and other languages. Studies of skipping in Chinese have tended to look at either only character skipping rates (Chen 1998), or 2-character words (Rayner, 2005) or one and two-character words (Rayner, 2006), so little is known about fixation probability for longer words. As mentioned above, studies of the effective field of vision in Chinese (e.g. Chen, 1998; Chen et al., 2003) have found that information can be obtained from 2-3 characters to the right of the current fixation. In this scenario, if the current fixation is on the first character of a 2-character word, then information can be obtained from the first, and possibly the second, character of the following word. This suggests that one and two character words could be processed parafoveally and we would expect equivalent skipping rates to other

languages.

### **Functorhood**

Two opposing predictions are possible with respect to a word's functorhood. Based on readers' intuitions, function words seem to play an important role in segmentation of text, which would suggest less frequent skipping and longer fixations. On the other hand, their position in the sentence makes them more predictable, on average, than content words, and therefore fixations might be expected to be shorter and the proportion of skips higher. We make the weak prediction that function words will either have longer duration measures and lower skipping rates, or shorter durations and higher skipping rates.



## **4 The Corpus**

### ***The 5-Language Corpus***

The 5-language corpus is a corpus of eye movement data collected from passage reading in five languages: Chinese, English, Spanish, Arabic and Hebrew. All materials were selected (with permission) from real newspaper articles. It is important to note that this is a natural language corpus. No attempt has been made to control for word length, frequency or any other variable. This is valuable because it means that the linguistic distributions herein reflect those naturally occurring in language. From the point of view of analysis, the linear mixed effects (LME) modeling method was implemented because it has the capacity to take subject and item variability into account simultaneously, and to accommodate graded variation in, for instance, word frequency, instead of simply assigning high and low frequency into bins and losing the gradedness along the frequency dimension.

### ***The corpus explored in the present study***

Between January 2005 and December 2007, the Chinese language corpus was compiled by researchers at the University of Edinburgh. Twenty-eight native speakers of Chinese (11 speakers of Taiwan Mandarin and 17 speakers of Hong Kong Cantonese) participated in the experiment for cash payment. Participants reported no vision problems other than astigmatism (1 participant), or near- or far-sightedness corrected by glasses (12 participants), contact lenses (6 participants) or laser surgery (1 participant). The age range was (26-38 years). There were (15) female participants and (13) male participants.

All materials were slightly edited versions of articles extracted from the on-line edition of the major Taiwanese national newspaper *United Daily News* between 16 August and 15 September, 2005. Although the spoken language differs between Taiwan and Hong Kong, the written language is very similar and it is commonplace for Hong Kong nationals to read news and other written material from Taiwan. Linguistic differences are expected to be comparable to differences

between dialects of other languages, such as English, for example. Both locations use traditional characters as their native writing system.

There were 21 news articles. Each article was divided into paragraphs, which were presented on separate screens. Each screen consisted of three to five lines. Line spacing was 108 pixels. Lines were not justified because all Chinese characters are of equal width. So each line had exactly 32 characters, except where the last line of the paragraph did not reach the end of the line. There was a total of 6432 words. (This is a slight over-estimate, because words that straddled two lines were counted as two separate words). Text was presented in traditional characters in 29-point PMingLiu font. Character width was 29 pixels and each character subtended 0.86 degrees of visual angle. No spaces were inserted between words or characters. Each article was followed by a *yes/no* comprehension question.

Word frequency information was obtained from the Academia Sinica online database ([http://elearning.ling.sinica.edu.tw/eng\\_teaching.html](http://elearning.ling.sinica.edu.tw/eng_teaching.html)).

### ***Insights from practical eye tracking experience***

Although the present corpus was compiled and completed prior to our analysis for the study presented here, we were able to draw insights about the implications of eye movement data from two types of practical eye tracking experience. Firstly, before work began on data analysis, a process of data cleaning was carried out to manually correct any discrepancies in the software output. This involved screen-by-screen examination of the fixation points for each participant, which in turn provided a vivid visual representation of typical eye movement patterns, as well as within-participant and cross-participant variation. (Only whole-line discrepancies were adjusted.)

In addition, involvement in a separate eye tracking study conducted over the summer provided insights into the actual process of conducting an eye tracking experiment, including the physical set-up of the equipment, the calibration process and other factors that might influence data collection, such as the

particular circumstances of individual participants. Data was collected for a binocular eye tracking study of lexical decision in word recognition. We were personally responsible for running 21 participants through to completion.

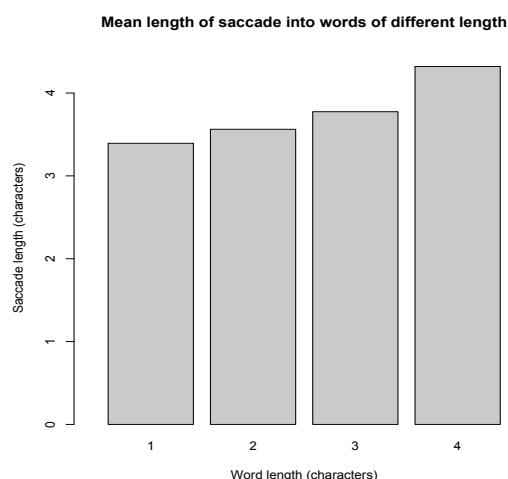
## 5 Results

### 5.1 Descriptives

Before embarking on a full analysis of results, an outline of general statistical descriptions is presented here of eye movement data and distributions within the corpus itself. This is to provide a natural history of the particular corpus under study, as read by these particular participants.

Average word length was 1.56 characters. Similar average word length was found in Academia Sinica Taiwan (1998) and previous studies (Yen et al., (2008). Average saccade length into a word was 3.53 characters. This is comparable to Feng et al.'s (2009) corpus of Chinese story reading by adults. Figure 1 shows mean saccade extent into words of different length. It appears that longer saccades are made into longer words.

Figure 1: Mean saccade extent into words of different length.



The average number of fixations per word was 0.55. This is lower than previous studies in Chinese (e.g. Perfetti and Tan, 1998). This may reflect the greater proportion of one-character words in the present corpus. For example, two thirds of Perfetti and Tan's (1998) data were two character words, with the remaining third divided among one-, three- and four character words. The average number of fixations (including regressions) by word length is shown in Figure 3. Word length seems to have a large influence on number of fixations,

with more fixations, on average, the more characters in the word.

Figure 2: Mean overall number of fixations by word length (including skipped words).

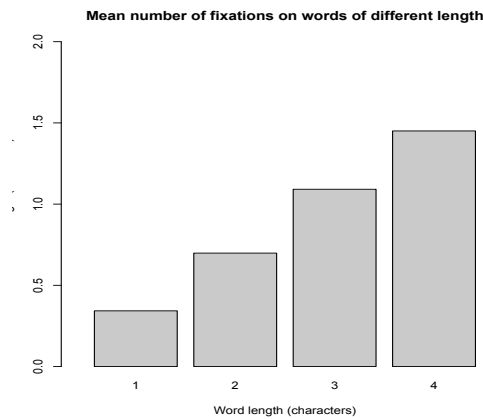
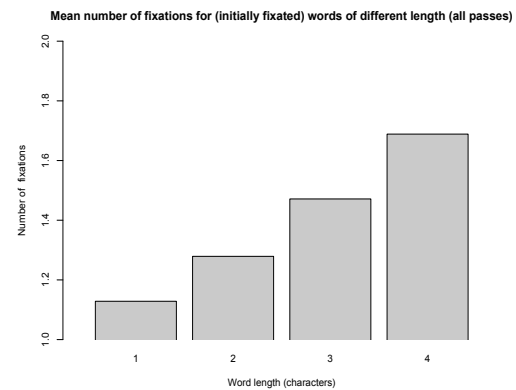


Figure 3: Mean fixation number by word length (calculated only for words initially fixated in first pass).



The overall rate of regression was 9%. This is a lower regression rate than has been found in most reading studies. Two factors might help explain this. Firstly, as mentioned above, the present corpus contains a high proportion of one-character words, which tend to be regressed to less often than longer words. Secondly, in the analysis, fixations that occurred after a line change were excluded, which may have led to under-reporting of regressions. This is particularly the case, since in passage reading, regressions may be made later than in sentence reading. Regression rate as a function of word length is shown in Figure 4. Fewer regressions seem to be made to shorter words.

Finally, total reading time by word length is shown in Figure 5. This measure includes all fixations in the first pass, as well as any subsequent passes (regressions). The overall time spent on a word seems to increase progressively as a function of word length.

Figure 4: Rate of regression to words of different length

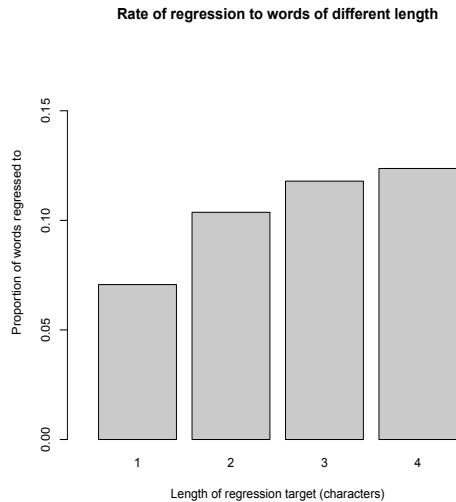
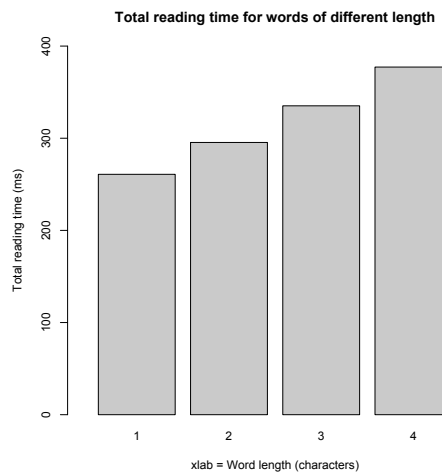


Figure 5: Total time spent on a word in all fixations, including regressions.



## 5.2 Data analysis

In this section, several measures are presented which have been selected for further analysis. For data analysis, three measures of eye movement behaviour in the first pass (first fixation duration, first pass gaze duration and likelihood of skipping a word in the first pass) were examined. First fixation duration is the length of time spent on the first fixation on a word in the first pass, regardless of whether it is the only fixation or whether there are subsequent refixations before the eyes leave the word. First pass gaze duration is the sum of all fixations on a word before the eyes move off the currently fixated word and onto another word. Therefore, it includes the first fixation duration and any subsequent refixations. (Here, a ‘refixation’ refers only to fixations that occur before the eyes leave the currently fixated word; if the eyes leave the current word and subsequently return to it, this is termed a ‘regression’.) For both viewing duration measures, calculation of the mean is dependent on the word being fixated in the first pass. Skipping rate is the proportion words not fixated in the first pass.

Effects of word length, functorhood and frequency on eye movement patterns were examined using linear mixed effects modeling (LME; Baayen, 2008; Baayen, Davidson & Bates, 2008). The LME approach has several advantages over the

traditional ANOVA approach (Yen et al., 2009). Firstly, since random effects from participants and items are included in the model, it has more power than methods that require separate (F1) analyses of participants and (F2) analyses of items (Baayen, 2008; Baayen, et al., 2008). Secondly, while traditional methods involve taking averages across participants and items prior to analysis, the LME approach is based on multiple regression from the full data set. It is therefore not as sensitive to different sample sizes due to missing data or unbalanced design.

The statistical procedure was implemented using R: A Language and Environment for an Statistical Computing (R Development Core Team, 2009; freely available at <http://cran.r-project.org>). Linear mixed regression analysis was conducted using the lmer programme (lme4 package; Bates, Maechler & Dai, 2008). The estimated effect size, standard error and t value were reported. P values were obtained through Markov chain Monte Carlo (MCMC) sampling for the durational measures. Because skipping responses were recorded as either skipped (1) or fixated (0), rate of skipping was calculated using the generalized linear model with binomial distribution and logistic link function.

For each of the three measures, First Fixation Duration, first pass Gaze duration and rate of Skipping, a series of lme analyses was consistently applied. Each new model was evaluated by comparing it to the previous model using an analysis of variance (ANOVA). Whichever of the models was revealed by the ANOVA to be the better of the two was selected for further analysis, and the other was rejected. Model 0 (fxtm 1) examined the main effect of Word Length on the variable under investigation. Model 1 (fxtm 2) investigated whether there was an effect of Word Frequency. The sequence of testing for the remaining models depended on the outcome of the existing models. Where both fixed effects Word Length and Word Frequency were reliable in the separate models, they were then both included together in the third model. If both were found to have reliable effects, a fourth model examined whether there was an interaction of Word Length and Word Frequency. Next the effect of Functorhood was examined in a separate model. If reliable, it was combined with the best of the previous

models. Finally, whether there was any interaction of Functorhood was investigated.

### **5.1.1 Variables**

Three first pass measures were selected for analysis. First pass measures were most important for the purposes of the present study, since first pass measures are considered to be associated with processing at the word level (. First Fixation Duration and Gaze duration were examined as durational measures are considered to reflect the level of difficulty involved in processing the fixated word. For example, a number of measures of difficulty, such as word frequency, predictability, neighbourhood size ... have been shown to affect the amount of time spent fixating a word in English and Chinese (Balota, Pollatsek, & Rayner, 1985; Binder, Pollatsek, & Rayner, 1999; Ehrlich & Rayner, 1981; Inhoff & Rayner, 1986; Juhasz & Rayner, 2003; Rayner & Duffy, 1986; Rayner, Sereno, & Raney, 1996; Schilling, Rayner, & Chumbley, 1998; Rayner & Well, 1996; Schustack, Ehrlich, & Rayner, 1987; Yan, Tian, Bai & Rayner, 2006; Yang & McConkie, 1999; Zola, 1984). Skipping was chosen as an example of a spatial/visiomotor measure.

Frequency was divided into five categories, from 1 (very low frequency) to 5 (very high frequency). Log frequencies ranged from -1.56019 to 10.4675 (per 10 million words). Each level contained equal numbers of tokens, or, where this would lead to the same token type straddling two frequency categories, the frequency category boundary was adjusted to the nearest token type boundary.

The functorhood variable had two levels: content words and function words (sometimes also referred to as 'open-' and 'closed-class' words, respectively). Content words included nouns, verbs, adjectives and most adverbs. (Some adverbs, such as 'then' and 'why' are also function words.) Function words included prepositions, pronouns, modal and auxiliary verbs, conjunctions,



determiners, grammatical particles, aspect markers, measure words and some adverbs. ('Measure words' are used before the noun in Chinese determiner phrases). The relative proportions were 64% content words to 36% function words.

Word length was measured in characters. The corpus contained 2816 (44%) one-character words, 3248 (51%) two-character, 310 (5%) three-character words and 51 (<1%) four-character words. These proportions are comparable to the estimated relative word length frequencies reported by Yen et al. (2008) calculated from the 10 million-word Academia Sinica Taiwan (1998) database. Longer words were excluded because they were too few to afford sufficient power for analyses. (A total of four, one and two 5-character, 6-character and 7-character words were excluded, respectively).

It is worth emphasising here that no attempt has been made to control for word length and frequency. Therefore, because the reading materials were taken from real-world samples, word length and frequency are confounded as they are in natural language. A result is that there are not equivalent data sets across all conditions. Indeed, some variables do not match across all other conditions. For example, related to the fact that four-character words are rare in Chinese in general, the four-character words in this study appear only in the *very-low frequency* category. Similarly, all the words in the *very-high frequency* category are one-character words. In addition, there were no four-character function words. This does not pose a problem for analysis, however, because the Linear Mixed Effects analysis is specifically designed to be able to deal with distributions such as this. MCMC simulations account for imprecision in the estimate of variance through multiple iterations (10 000 iterations in the present analyses) of sampling of conditional distributions of subsets in a cycle (Baayen & Bates, 2009).

### **5.1.2 Exclusions**

There were a number of data points that were excluded from analysis. Fixations that fell on punctuation marks or the 'END' box at the bottom of the page, which marks the end of the passage, were excluded. Words for which the boundary had been incorrectly marked in the original xml files, or which straddled two lines, were not included in analysis (6%). Fixations that were under 50 ms or over 1000 ms were excluded (<0.001%).

Fixations that occurred before or after a line change and fixations on the first and last characters of each line were excluded from analysis (7%). This is because return sweeps from the end of one line to the beginning of the next often undershoot, leading readers to make small, corrective regressive saccades. In previous reading studies in English it has been found that both the first and last fixations on each line tend to be around 5-7 letter spaces from the edge of the text (Rayner, 1998). The duration of these fixations differs from other fixations, with the first fixation tending to be longer and the last fixation shorter than fixations in the rest of the line (Heller, 1982; Rayner, 1977; Rayner, 1978). Words longer than 4 characters were not analysed, because the numbers were too small (see above for exact numbers). Fixations that occurred before or after a blink were excluded because movement of the eyelids can cause inaccuracies in recording of the fixation location. Finally, although recording was binocular, only right-eye fixations were analysed. For first fixation duration and first pass gaze duration, tokens on which there were no fixations in the first pass were excluded from calculations (i.e. calculations of means were based on fixated tokens only).

## **5.2 Analyses**

### **5.2.1 First fixation duration**

Mean first fixation duration across all tokens and participants was 234 ms. Figures 1-5 show mean first fixation duration as a function of the three fixed effects examined (i.e. Word Length, Word Frequency and Functorhood) and combinations thereof. The mean First Fixation Durations for words of different length are shown in Figure 1. The time spent initially fixating four-character words seems to be slightly longer than for the shorter words. Indeed, although

this effect was very small, and LME analysis of Model 0 (fxtm 1) revealed a reliable effect of Word Length (see Table 1).

The effect of word frequency on first fixation duration is shown in Figure 2. The figure indicates that the time spent on a word in the initial fixation decreased with each increase in frequency from 1 (very-low frequency words) up to 5 (very-high frequency words). In fact, the frequency effect was confirmed in an analysis using LME, which showed a reliable effect of Word Frequency on First Fixation Duration (see Table 1).

Figure 6: First fixation duration (ms) for words of different length (characters)

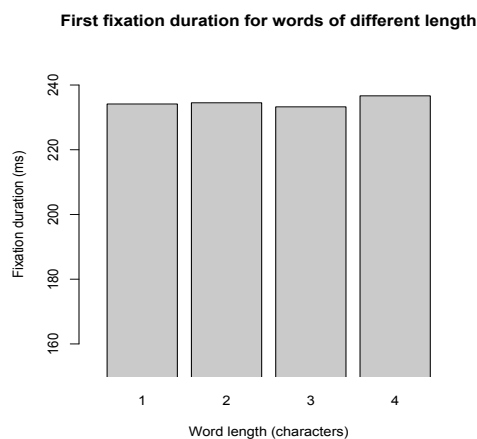
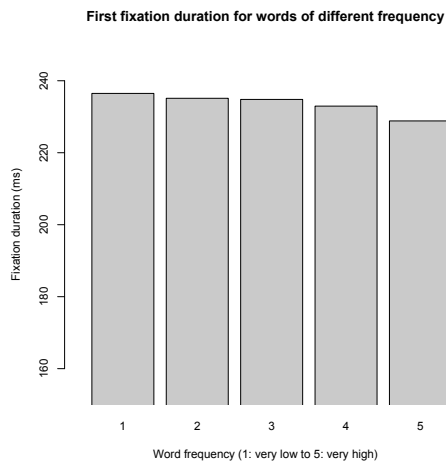


Figure 7: First fixation duration (ms) for words of different frequency. Frequency increases left to right: very-low frequency words (1) to very-high frequency words (5).



First fixation duration as a function of Word Frequency and Word Length is represented in Figure 3. Word length (in characters; 1-4) is shown in the four separate columns. Word frequency is represented in the shading scheme shown in the legend, with Frequency 1 (very-low frequency) represented in the darkest grey, through to the lightest shade representing Frequency 5 (very-high

frequency). As Table 1 shows, an ANOVA revealed the model (model 2; fxtm3) was significantly improved when both word frequency and word length were included ( $\chi^2 = 17.679, p=0$ ).

The teasing apart of Word Length and Word Frequency effects reveals a very interesting trend. As expected, for words that are one or two characters long, initial fixation durations on higher frequency words are shorter than fixations on lower frequency words. Counter-intuitively, for words of the same frequency, the time spent initially fixating a word actually appears to decrease in longer words compared to shorter words, especially between one- and two-character words, and between two- and three-character words. For example, the mean first fixation duration for very-low frequency one-character words is around 7ms longer than for their two-character word counterparts; a similar trend is found in the higher frequency words. The pattern becomes less clear with the longer words. There seems to be a trend for fixation durations to increase slightly for longer, lower-frequency words, compared to the shorter counterparts. (All the four-character words in the corpus are very-low frequency, so no frequency effect can be examined within the four-character word group.) To further investigate the relationship between Word Length, Frequency, and First Fixation Duration, an interaction of Word Length and Word Frequency was implemented in the model. However, an ANOVA revealed that the model was not significantly improved compared to the previous model. This indicates that both factors play a role in First Fixation Duration, but they do not interact to produce this effect.

Figure 8: First fixation duration (ms) for words of different length (characters) and frequency. Length increases in the four columns, left to right. Frequency is represented in shades from dark to light (see legend) with increasing frequency increases left to right: very-low frequency words (1) to very-high frequency words (5).

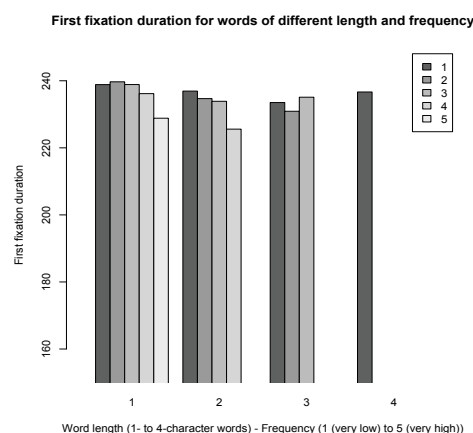


Figure 9: First fixation duration as a function of word length

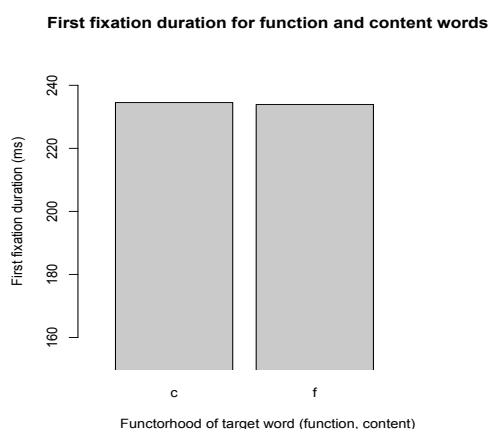


Figure 4 shows the effect of functorhood (whether a word is a function word or a content word) on mean first fixation duration. Although the overall mean for Function words does not seem to differ from that of the Content words, an ANOVA showed that adding the FC variable to the model did improve it significantly ( $\chi^2 = 6.3858$ ,  $p < 0.05$ ). However, it diffused the effects of word length and frequency, and in fact, functorhood per se did not reach significance level. To further explore the effects of FC, I examined how it interacted with word length (TokenLen) and word frequency (fq). There was no significant interaction.

Figure 5 demonstrates the effects of all three fixed effects, Word Length, Word Frequency and Functorhood. Each panel represents the different word lengths (in characters), increasing from left to right, bottom to top. The shades of colour represent the five Word Frequency categories, from very-low frequency on the left (pale blue) to very-high frequency on the right (grey-blue). Within each panel, the columns of Frequency bars are grouped by Functorhood, with Content words (c) on the left and Function words (f) on the right. The effect of Functorhood on first fixation duration is most evident in three-character words (top left panel). Three-character Function words seem to have substantially shorter initial fixations than their Content word counterparts. This difference in

initial fixation duration becomes inflated as Word Frequency increases from very-low frequency to medium-low frequency. Word Frequency seems to have an effect for the Function Words, but there does not appear to be any difference in the means for Content words of different frequency. The mean duration of initial fixations on Function words decreased between the very-low and the medium-low frequency categories, whereas there was virtually no difference in the means for Content words between these frequency categories. Interactions between the fixed effects were explored by adding a three-way interaction to the model. However, an ANOVA showed no significant improvement of the model after inclusion of the interaction.

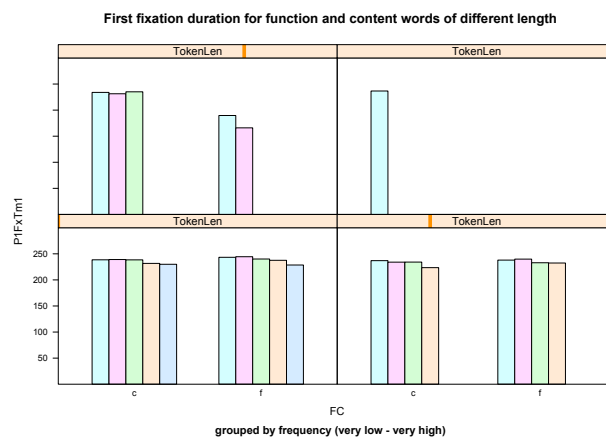


Figure 10: First Fixation Duration (P1FxTm1; ms) by Word Length, Word Frequency and Functorhood. Word Length (characters) is shown in the panels from left to right, bottom to top: 1-char words bottom left, 2-char words bottom right, 3-char words top left, 4-char words top right. The five Word Frequency categories are shown in colour shades, from very-low frequency, left (pale blue), to very-high frequency, right (grey-blue). Within each panel, columns are grouped by Functorhood: Content words (c), left, and Function words (f).

Finally, significance testing for Word Length and Word Frequency established that both were significant (see Table 1). Functorhood did not reach significance.

In sum, First Fixation Duration showed significant effects of Word Length and Word Frequency. There was no significant interaction. The effect of Functorhood did not reach significance.

Table 1: The estimate, standard error, t value and p (repeated measure) for model 6 (fxm 7) of the LME analysis for the fixed effects Word Length (TokenLen), Word Frequency (fq) and Functorhood (FC) for First Fixation Duration. The p values were obtained through Markov chain Monte Carlo (MCMC) sampling. Values in bold type did not reach significance.

Measure	Fixed Effects	Estimate	Standard Error	t value	P (rep)
First fixation duration	TokenLen	-3.811	0.9062	-3.84	0
	fq	-2.9475	0.3916	-7.54	0
	<b>FC</b>	<b>-1.6098</b>	<b>0.8847</b>	<b>1.56</b>	<b>0.13</b>

### ***5.3 First pass gaze duration***

The overall mean first pass Gaze duration for all participants and tokens was 254 ms. The effects of Word Length, Word Frequency and Functorhood on Gaze duration are shown in Figures 6-9. In Figure 6, mean Gaze duration is shown as a function of Word Length. Gaze seems to increase substantially as Word Length increases. In addition, the size of the effect appears to increase with every additional character. In other words, there is a greater increase in the mean Gaze duration between three- and four-character words than between two- and three-character words, and between two- and three-character words than between one- and two-character words. Not surprisingly, the LME analysis revealed a reliable effect of Word Length (see Table 2).

It should be noted that since Gaze Duration includes first fixation on a word, it is not entirely independent of First Fixation Duration. As a consequence, given the relatively small Word Length differences in First Fixation measure, the Word Length differences seen in Gaze Duration largely reflect the likelihood of refixation (as well as duration of refixations) on the word in the first pass. It is beyond the scope of the present paper to examine the phenomenon of refixation

in depth and statistical analyses have not been carried out, however, general descriptive statistics are outlined above.

Figure 11: Gaze duration as a function of Word Length

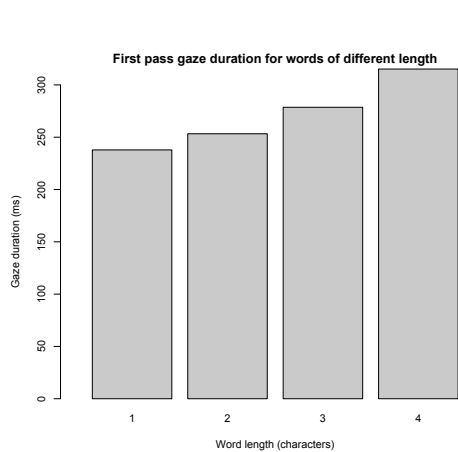


Figure 12: Gaze duration as a function of Word Frequency. From left to right: very-low frequency words (1) to very-high frequency words (5).

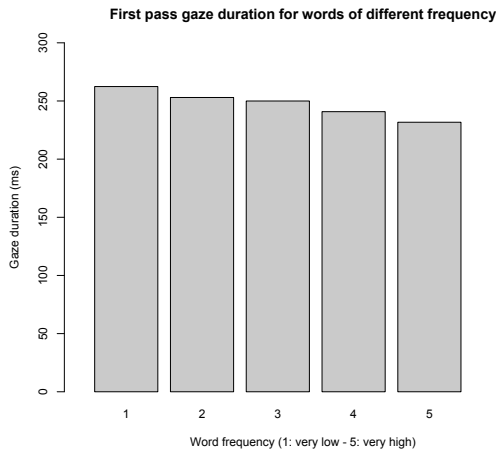


Figure 11b: Plotmeans of gaze by word length. Figure 12b: Plotmeans of gaze by word frequency

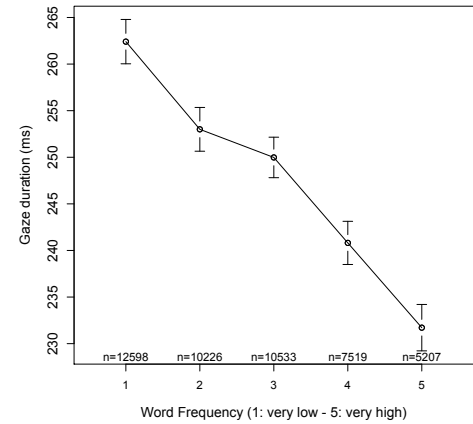
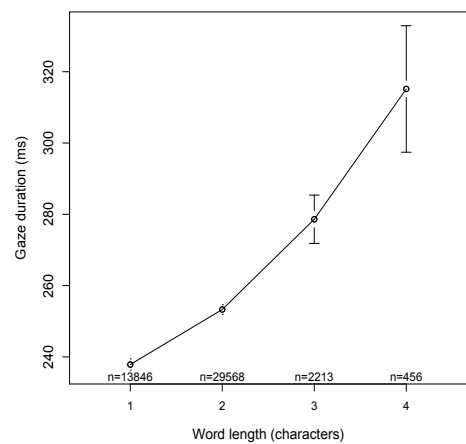


Figure 7 shows the effect of Word Frequency on Gaze duration. The differences in means suggest that, generally speaking, the lower the frequency of a word, the longer readers spend fixating it. Indeed, an LME analysis showed a reliable effect of Word Frequency on Gaze duration. As with Word Length, the greater Word Frequency effect on Gaze duration compared with First Fixation Duration is likely to reflect the probability of refixation on the word.



Figure 8 shows the combined effects of Word Length and Word Frequency on Gaze duration. The different Word Length categories are shown in shades of grey, from dark to light with increasing word length (see legend). Word Frequency increases from left (1: very-low frequency) to right (5: very-high frequency). The Word Length effect, shown in Figure 6, seems to remain strong within the Word Frequency bands. In general, within each level of frequency, the longer a word is, the longer readers spend fixating it. This is particularly evident in the very-low frequency category, where all word lengths are represented, but there is also a clear trend in the medium-low and medium frequency categories. The difference in means across frequencies suggests that Word Frequency has a smaller effect on Gaze duration compared Word Length, though it still came out as reliable (see Table 2). The relationship between these variables was examined statistically with an LME analysis that included both Word Length and Word Frequency in the model of Gaze duration (model 2; gaze3). This lead to a very significant improvement in the model ( $\text{Chisq} = 129.73$ ,  $p=0$ ).

The relationship between the effects of Word Length and Word Frequency on Gaze duration was further investigated by adding a two-way interaction into the model. An ANOVA found the inclusion of the interaction in model 3 (gaze4) lead to a significant improvement over the previous the model ( $\text{Chisq} = 44.647$ ,  $p = 0$ ). First pass gaze duration was the only measure for which there was a reliable interaction of Word Length and Word Frequency.

Figure 8a: Gaze duration as a function of Word length, grouped by Word Frequency. The legend shows the grey scale for words of length 1-4 characters. Word Frequency is shown in the separate columns (1: very-low to 5: very high).

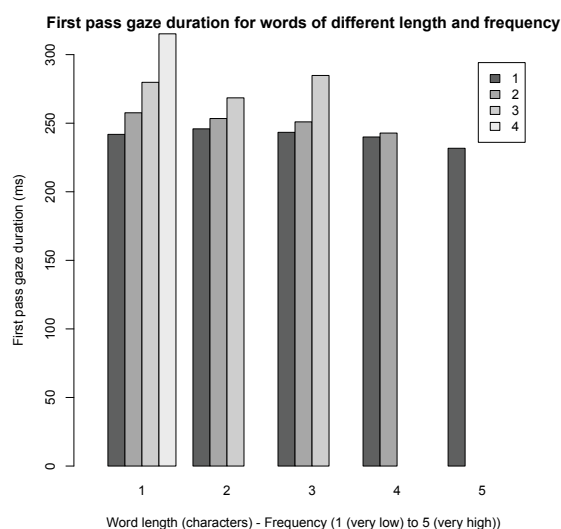
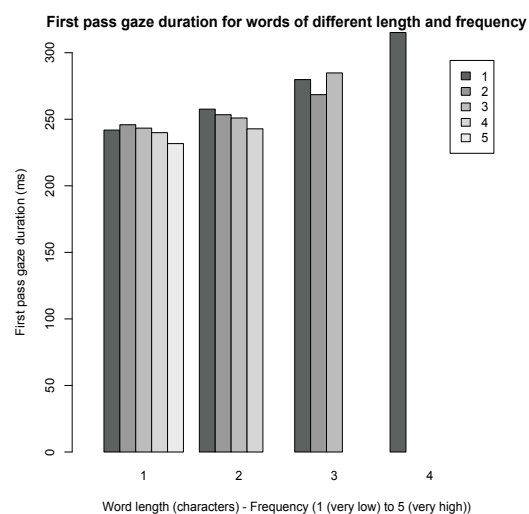


Figure 8b: As in Figure 8b, Gaze duration is shown as a function of Word length and Word Frequency. Grouping by Length. The legend shows the grey scale for Frequencies 1-5 characters. Word Length is shown in the separate columns.



Gaze duration as a function of Functorhood is shown in Figure 9. Figure 10 shows the effect of Functorhood and Word length. In Figure 9, there seems to be a difference in mean Gaze duration between Content and Function words. However, analysis with LME revealed this effect was not reliable. In Figure 10, it becomes clear that when word length is accounted for, the means are almost identical across the Function and Content categories. Longer durations in the Content word category only occur for the four-character words. As there are no four-character Function words, this leads to a greater overall mean for Content words.

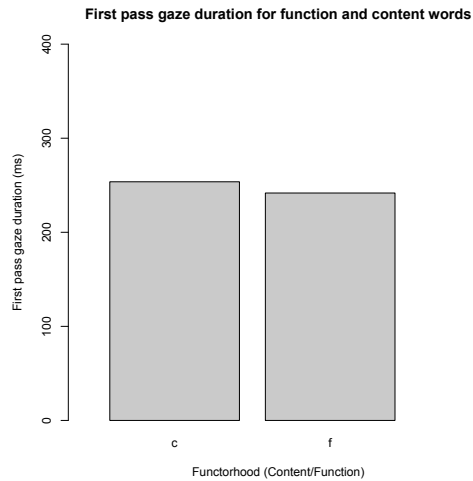


Figure 9: Gaze duration as a function of functorhood.

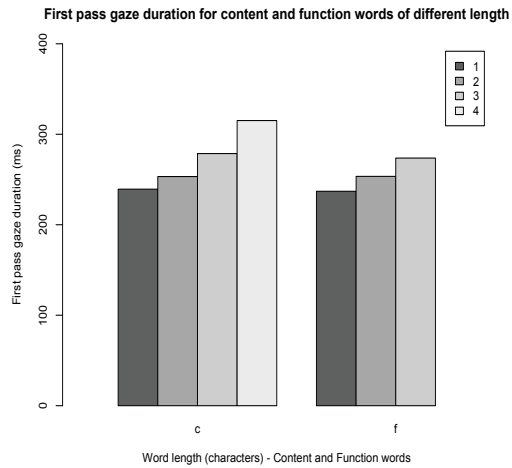


Figure 10: Gaze duration as a function of Functorhood and Word Length

To summarise, only Word Length had a significant main effect on gaze duration. There was also a highly significant interaction of Word Length and Word Frequency.

Table 2: Estimate, standard error, t value and P (repeated measure) for the fixed effects of Word Length (TokenLen), Word Frequency (fq) and their interaction in model 3 (gaze4) for Gaze duration. Values in bold type did not reach significance.

Measure	Fixed Effects	Estimate	Standard Error	t value	P (rep)
P1 gaze duration	TokenLen	66.1341	1.6908	39.11	0
	<b>fq</b>	<b>1.1892</b>	<b>0.8827</b>	<b>1.35</b>	<b>0.17</b>
	TokenLen*fq	-3.7918	0.5674	-6.68	0

## 5.4 Skipping

The overall proportion of words skipped in the first pass was 62%. Figures 11-13 show the proportion of words initially skipped in the different bins. Figure 11 shows first pass Skipping Rate as a function of Word Length. The proportion of

skipped words varied substantially as a function of their length. One-character words were skipped a majority of the time (77%). The proportion of skips decreased rapidly as the words became shorter. Two- and three-character words were skipped 53% and 32% of the time, respectively, and four-character words were skipped a much less frequent, though still substantial, 19% of the time. As expected, an LME analysis of model 0 (skip1) revealed a very robust Word Length effect.

In Figure 12, the proportion of first pass skips is shown for words of different frequency. The Skipping Rate seems to increase steadily with each increase in Word Frequency. Indeed, a reliable Word Frequency effect was established with an LME analysis (model 1; skip2). Very low frequency words were skipped 50% of the time, while as much as 78% of very high frequency words were skipped. Word Frequency was compared to Word Length as a model of variance in Skipping rates. In fact, the ANOVA found Word Frequency to be a significantly better fit than Word Length.

Figure 13: Rate of skipping by word length

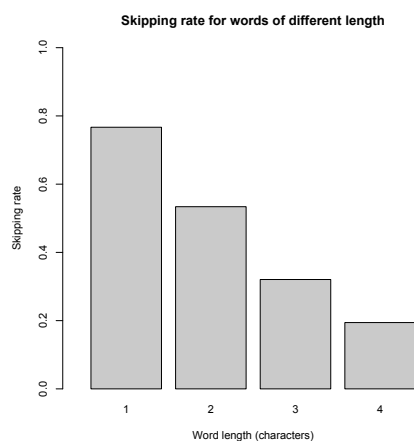


Figure 14: Rate of skipping by word frequency.

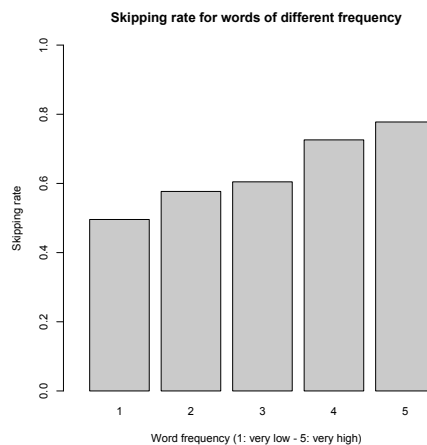


Figure 13b: Plotmeans of rate of skipping by word length

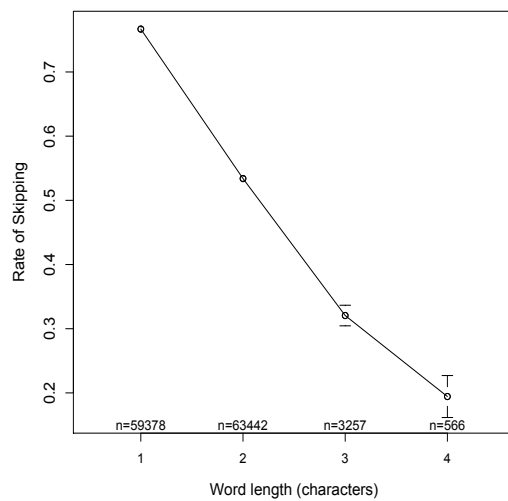
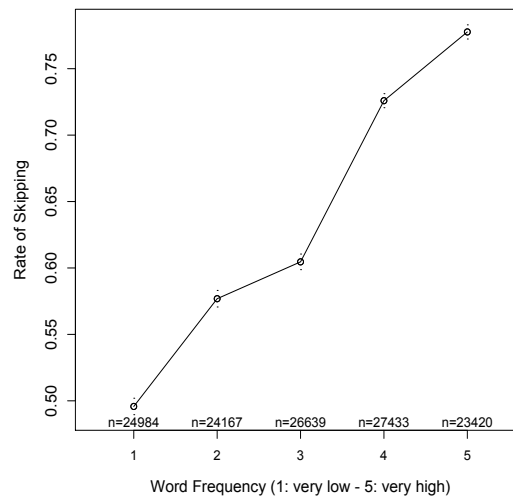


Figure 14b: Plotmeans of rate of skipping by word frequency



In Figure 13, Skipping rate is represented as a function of Word Length and Word Frequency. Word Frequency is shown in the five shades of grey (see legend), with bars grouped by Word Length. Within each of the Word Length groups 1, 2 and 3, there is a visible trend of higher proportions of Skips as Word Frequency increases. (Word Frequency cannot be examined for 4-character words, since they only occur in the lowest frequency category). In terms of Word Length, there was a large decline in the rate of Skipping with each additional character in the word, and this was moderated by Word Frequency.

The effects of Word Length and Word Frequency were investigated statistically by including both fixed effects in the model. Inclusion of both effects did, in fact, significantly improve the model (Chisq = 118.54,  $p=0$ ). An ANOVA showed there was no significant improvement when Word Length and Word Frequency were modelled as an interaction.

Figure 15: Rate of skipping as a function of word length and frequency

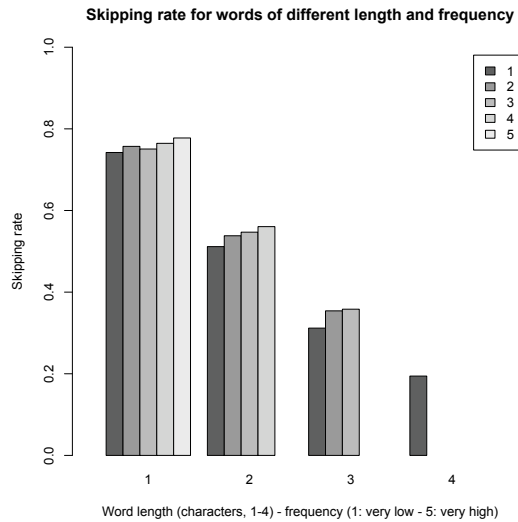
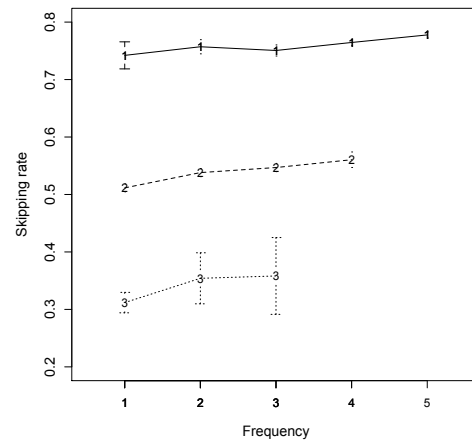


Figure 15b: Plotmeans of rate of skipping as a function of word length and frequency



The effects of Functorhood on Skipping rate were also investigated. Figure 14 shows the proportion of Content and Function Words that were initially skipped. On first inspection, it appears that Function Words are skipped much more often than Content Words. Indeed, an LME model that included only Functorhood found it to have a reliable effect on Skipping rate. However, when Functorhood is examined together with Word Length, its effect on Skipping rate seems to disappear (Figure 15). In fact, when Functorhood was added to the existing model with Word Length and Frequency, there was no significant improvement in the model.

Figure 16: Rate of skipping by functorhood

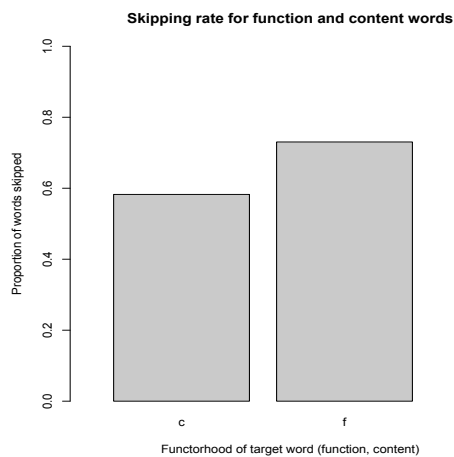


Figure 16b: Plotmeans of rate of skipping by functorhood

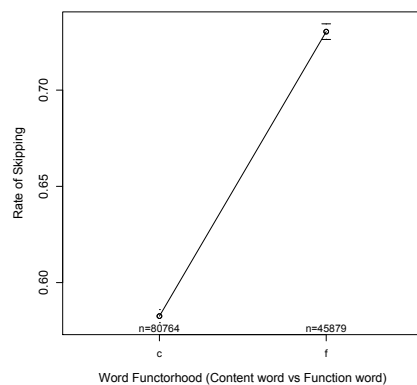
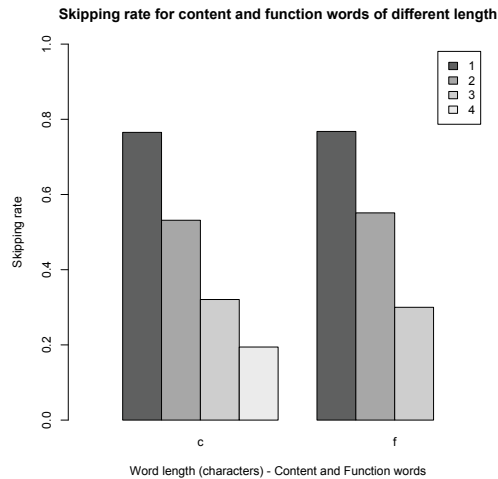


Figure 17: Rate of skipping as a function of word length and functorhood



Overall, it appears that, of the fixed effects investigated, the most important factor in whether a word is fixated in the first pass is its length. In addition, words of any length (at least up to three characters) are more likely to be skipped the higher their frequency.

Measure	Fixed Effects	Estimate	Standard Error	t value	P
Skipping	TokenLen	-0.958599	0.015616	-61.39	0
	fq	0.067898	0.006231	10.9	0

## Landing position distributions

Figure 18 shows the landing position distribution for words of different length. Interestingly, the distribution is very skewed to the left. For two-char words, more than two thirds of fixations are on the first character. Landing positions in the longer words preserve this leftward pattern, with almost all fixations on the first two characters. Also interesting is that, although very few fixations land on the third character, there is a higher proportion of fixations on the second character, compared to two-character words. In other words, there is a small

rightward shift in the longer words. Figure 19 shows landing position as a function of word length and frequency. There does not appear to be a clear effect of frequency.

Figure 18: Landing position distribution

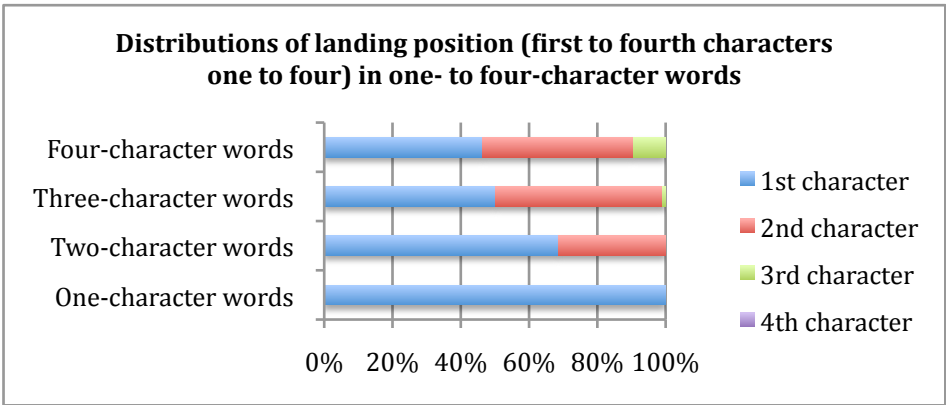


Figure 18b: Plot means of landing position distributions for 2-4 character words

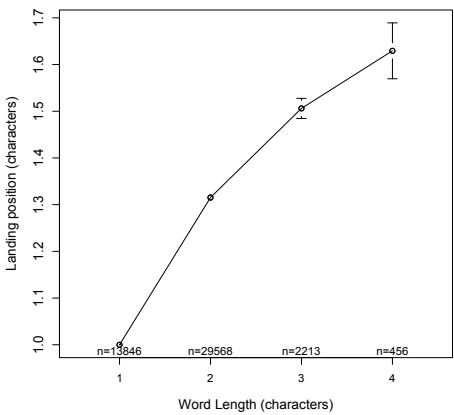
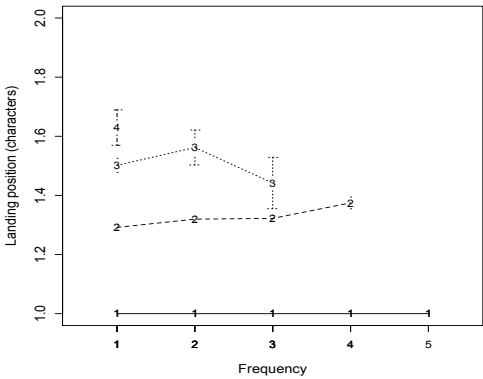


Figure 19: Plot means of landing position distribution by word length and frequency





## Post-hoc analysis of effect of fixation number of first fixation duration

Initial analysis of first fixation duration revealed a surprising trend that in most cases, shorter words seemed to be fixated for longer than long words of the same frequency (see Figure 8). To further investigate this phenomenon first fixation duration was divided into two categories: fixations that were the only fixation in the first pass (single fixation) and the first of two or more fixations in the first pass (first of multiple fixations). Figures 20 and 21 show the fixation durations for single fixations and first of multiple fixations, respectively. There is a substantial increase in fixation time for the first fixation when it is followed by other fixations in the same word in the first pass, compared to single fixation durations. Number of first pass fixations was added to the model for first fixation duration to test whether it improved the model. An ANOVA showed a significant improvement in the model by including fixation number ( $\chi^2 = 102.8, p=0$ ). An LME analysis was then conducted to test the new model (fxtm15). Fixation number was found to be significant.

Figure 20: Fixation durations for single fixations on words of different length

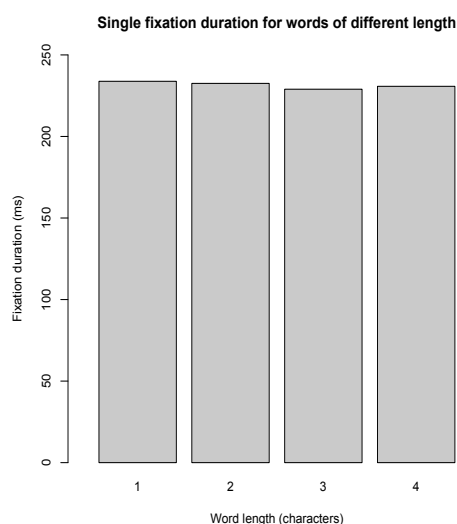


Figure 21: Fixation durations for the first of multiple fixations on words of different length

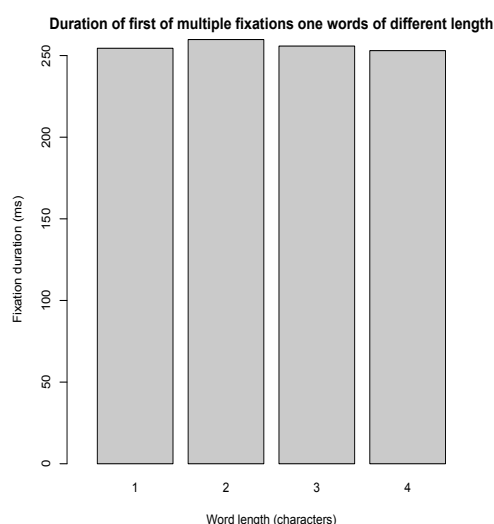


Figure 22: Duration of first of multiple fixations, by word length and frequency

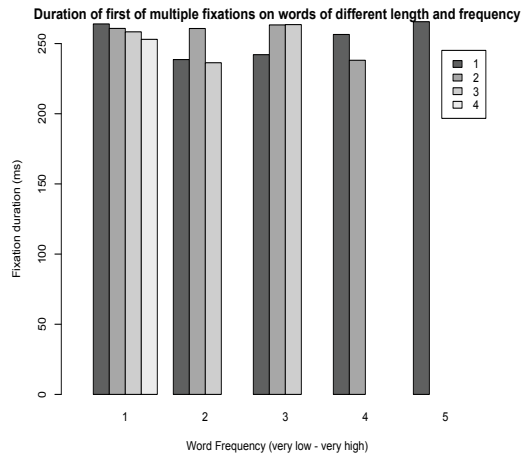


Figure 23: Duration of single fixations by word length and frequency

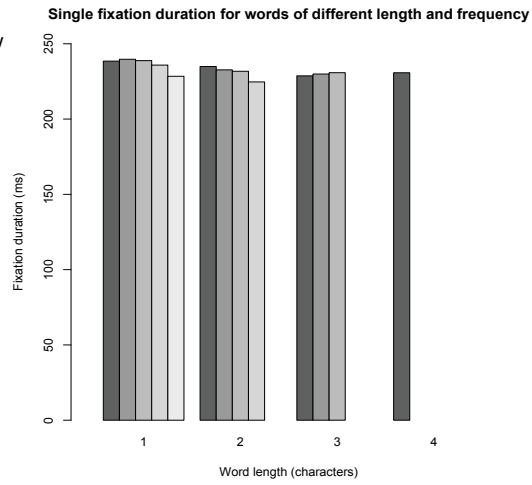


Table 4: The estimate, standard error, t value and p (repeated measure) for model 14 (fxtm15) of the LME analysis for the fixed effects Word Length (TokenLen), Word Frequency (fq) and Functorhood (FC) for First Fixation Duration, and number of fixations. The p values were obtained through Markov chain Monte Carlo (MCMC) sampling. Values in bold type did not reach significance.

Measure	Fixed Effects	Estimate	Standard Error	t value	P (rep)
First fixation duration	TokenLen	-3.71	0.93	-3.84	0
	fq	-3.16	0.42	-7.54	0
	<b>FC</b>	<b>-1.58</b>	<b>1.11</b>	<b>1.56</b>	<b>0.13</b>
	Fixation number	14.90	<b>1.47</b>	<b>10.14</b>	0

## **6 Discussion**

The purpose of the present study was to explore some of the basic eye movement patterns involved in natural reading of Chinese text. The durational measures first fixation duration and first pass gaze, as well as the proportion of words initially skipped were examined as functions of word length, word frequency and functorhood. Landing position was examined as a function of word length. Post-hoc analyses investigated the effect of the number of first pass fixations on first fixation duration. The central findings of the analyses were as follows: (1) word length had a robust main effect on all three measures; (2) word frequency also very significantly influenced the time spent initially fixating a word, but the effect was generally smaller than that of word length; (3) for first pass gaze duration there was no main effect of word frequency, but a significant interaction of word length and frequency; (4) the number of first pass fixations affected first fixation duration, with less time spent on single fixations than on the first of several fixations; (5) landing positions fell predominantly at the beginning of words, and also showed word length effects; (6) functorhood had no significant effect on any of the measures.

### **First fixation duration**

Analysis of the duration measures yielded some interesting and surprising results. Firstly, as expected, our prediction that overall mean first fixation duration would be similar to previous findings in English and Chinese was upheld. Also as expected, word length influenced the time readers spent initially fixating a word. The effect was rather small, and was mainly evident in longer durations for four-character words. The word-effect prediction was supported by the finding that frequency also influenced initial fixation time, with moderately shorter durations for higher-frequency words, compared with lower-frequency words.

When word length and frequency are considered together, differential effects are inflated and an interesting pattern emerges. It appears that the two effects influence fixation durations in opposite directions; since word length and frequency are confounded, the additive effects seem to cancel each other out to a

large extent, so that the independent effects look rather flat. Within each word length category, higher frequency is correlated with lower fixation times. Interestingly, within the frequency categories, longer words seem to have shorter, rather than longer fixation durations.

Since the initial fixation on longer words is quicker than on short words, this suggested the possibility that this was related to the number of fixations; longer words are more likely to be refixated, and therefore, initial fixations may have been terminated early, as suggested in the IOVP (Vitu, McConkie, Kerr & O'Regan, 2001), and O'Regan's (1990, 1993) strategy-tactics theory.

O'Regan proposed that readers implement both a global strategy and local within-word tactics. For example, readers might adopt a careful or risky reading strategy, which would have a coarse-grained influence on eye movement measures, such as overall fixation times and saccade lengths. On the other hand, he suggests that lower-level nonlexical information obtained about specific words early in a fixation influence within-word tactics. If the eyes land near the centre of the word, where viewing is optimal, the word will be fixated only once. The fixation will be maintained until word identification is complete. In O'Regan's (1990, 1992) model, the time taken for processing within each fixation is assumed to be constant, irrespective of its within-word location. A flat curve is predicted for first fixation durations, as well as double-fixation gaze durations. In the IOVP model, the duration of fixations is also influence by landing site and related to fixation number. This is surprising in light of previous findings in other languages. According to the IOVP, optimal fixations, those near the centre are longer than those near the beginning or ends of words.

Prior to or during initial fixation on a word, readers assess whether a further fixation is needed for word identification: if it is required, the initial fixation is terminated early and the eyes refixate within the same word; if, on the other hand, a single fixation is sufficient for word identification, more time is spent on the initial fixation so that sufficient processing can be completed before the eyes move off onto another word.

However, analysis of first fixation duration as a function of number of fixations (single or multiple) revealed the opposite pattern. Unexpectedly, single fixations were shorter than multiple fixations, and each had a rather flat distribution by word length. It is unclear what mechanism is responsible for this phenomenon. There are two possible explanations. Firstly, another independent effect, such as predictability, might be influencing both the initial fixation duration and the refixation probability. The somewhat erratic pattern in the multiple fixation durations suggests this possibility. A second explanation is that there is a kind of default setting of one fixation per (fixated) word in place for saccade targeting. If a second within-word fixation is required, there is an extra processing cost for cancelling the outward saccade and planning a refixation. Determining which of these explanations is correct is beyond the scope of this study. However, given the brevity of Chinese words and the low number of actual refixations in the data, a single-fixation default saccade targeting strategy may be a plausible explanation for the eye movement patterns reported here.

### **Gaze duration**

As expected, the differences in gaze durations show that the more characters a word contains, the longer readers spent looking at it. This was true for each increase in length, from one to four characters. Because the gaze duration measure includes the first and any subsequent fixations on a word in the first pass, the differential word length results reflect the number of first pass fixations. Generally, the longer a word is, the more likely readers are to fixate on the word a second or subsequent times.

However, in contrast to previous findings, as mentioned above, longer first fixation durations were found for refixated words. This means that, for refixated words, gaze duration increased not only due to refixation time, but an extra 20 ms on average will result from longer durations of the initial fixation.

The word length effect was modulated by word frequency. Word frequency on its own did not reliably affect gaze durations, but for a given word length, particularly for one- and two-character words, higher frequency words were

fixated more briefly than lower frequency words. There are two possible explanations for the lack of frequency effect on gaze durations, and possibly both factors are at work. Firstly, frequency categories were created by dividing all tokens in the corpus into five equal groups. This may have led to a broad spread of frequencies within some categories, and therefore relatively moderate differences between the frequency categories, compared to experiments that specifically select words that are typical exemplars of word frequency categories. Related to this, the division into five categories, rather than three, as some studies have done, is likely to weaken effects.

The second explanation has to do with the reading format. As discussed above, reading of passages and reading of sentences tend to produce quantitatively different eye movement measures. Consistent with the present results, Radach et al. (2008) found that gaze durations were shorter in passage reading, as compared to sentence reading. They suggest this is the result of relatively quick, superficial processing in the first pass, which is then compensated for with more frequent regressions for integrating contextual information. Since more contextual information is available in passage reading, predictability effects may override frequency effects to some extent, and processing relies more on context than on language-global frequency statistics.

### **Landing position**

One of the most interesting and surprising results to come out of this investigation was the finding of a word-based landing position distribution. That is, saccades consistently landed between the beginning and the centre of a word. For two-character words, two thirds of fixations were on the first character. In three- and four-character words, there were fewer fixations on the first character – around half – but almost all fixations were on the first or second character. Around 10% of fixations on four-character words, and only about 1% of those on three-character words were on the third character. This suggests two things. Firstly, there is a strong tendency to fixate near the beginning of a word, or between the beginning and the middle. And, secondly, that word length had an influence on saccade landing sites, leading to a rightward shift in longer words.

Based on landing distributions in alphabetic languages, these results might not seem surprising. After all, this pattern quite closely resembles the results reported regarding the preferred viewing location (Rayner, 1979). However, several studies of Chinese reading have failed to find a preferred viewing position in Chinese (e.g. Chen et al., 2003; Tsai & McConkie, 2003). The explanation for this discrepancy in results is unclear, but may lie in the presentation of materials. In these studies, words were interspersed with white spaces, which do not appear in normal reading. This may have interrupted saccade planning or made it unnecessary to adopt a word segmentation-based saccade targeting.

## **Skipping**

The proportion of words skipped in the first pass was generally remarkably high. Firstly, one-character words were skipped most of the time. This is consistent previous findings that short words are not usually fixated. For example, 2-3 letter English words are skipped around 70% of the time (Starr & Rayner, 2001).

## **The Lexical Segmentation Hypothesis**

A number of predictions made by the LSH were supported. Firstly, landing position distributions show a strong word targeting effect, with a consistent pattern of left-of-centre fixation location. The great majority of fixations fell on the first or second character; however, word length was found to influence saccade landing sites in a rightward direction for longer words. The combination of these two effects suggests a word-based saccade targeting strategy.

An interesting - and puzzling - recent finding in Chinese reading relates to the type of information that can be extracted from the right of fixation. It is well established that in English although orthographic and phonological information are available during parafoveal processing, no semantic information can be obtained before foveation. However, a number of studies have found semantic preview effects in Chinese. For example, using the contingent display technique, Yen et al. (2008) presented participants with ambiguous characters, whose

meaning was altered depending on the word they appeared in. Parafoveal preview effects were obtained for the particular word-specific character meaning, but not the irrelevant character meaning. The answer to the question of why semantic information might be available to readers of Chinese, but not for other languages has remained elusive. We believe the LSH provides a plausible explanation for this finding.

In a regression study using a corpus of English and French passage reading, Pynte and Kennedy (2006) found that global measures, independent of and not immediately related to words currently in the perceptual span had significant effects on all of the durational and spatial eye movement measures they examined (inter-word saccade latency, saccade extent, probability of skipping, as well as number of fixations, first fixation and gaze durations). They found that language-specific, global statistics seemed to affect which properties of words in the parafovea influenced duration of foveal inspection of the currently fixated word. For example, for English, fixation duration varied as a function of the frequency of the word in the parafovea, while in French foveal inspection time was influenced by the informativeness of the initial trigram in the parafovea. Pynte and Kennedy argue that readers become accustomed to the word length statistics of their language, and that this shapes the process of parafoveal inspection so that only information that is statistically likely to be useful in a particular language is attended to parafoveally. Similarly, there is evidence that morphological information available in the parafovea provides a preview benefit in Hebrew (see Deutsch, Frost, Peleg, Pollatsek, & Rayner, 2003; Deutsch, Frost, Pollatsek, & Rayner, 2000, 2005).

### **The Lexical Segmentation Hypothesis**

Parafoveal word segmentation is easier in Chinese because of reliable character-syllable mapping.



## **Summary and Conclusions**

Given the vastly different codes by which language is represented in text across languages, the findings discussed here serve as a reminder of the remarkable flexibility of reading skill. In conjunction with findings from previous studies in English and other alphabetic languages, the reported results indicate some of the various ways in which eye movements and the underlying cognitive and visual systems align themselves to accommodate the features and characteristics of the specific language and orthography at hand.

## **Future Work**

The present study has led to important findings in Chinese reading research. In the immediate future, follow-up work will include drawing up papers for publication on results relating to skipping rates; durational measures, particularly with respect to single fixation duration and first of multiple fixations; and landing position distributions.

In continuing research, we plan to investigate binocular eye movement measures. For example, the results presented herein show relatively high rates of skipping, with calculations based on fixations made with the right eye only. It is likely that the overall skipping rate would be substantially lower if left-eye fixations were included. Durational measures are also expected to vary as a function of whether a fixation is binocular (both eyes on the same word) or monocular (only one eye on a particular word). Further investigation is needed to verify these predictions. If they are correct, it will have major implications for current reading models.

In addition, a number of other measures require examination in order to build the present results into a richer, more detailed picture of eye movement characteristics in Chinese reading. In particular, due to time restrictions, in the interests of simplicity, inter-line saccades were excluded from analysis. However,

these may be of interest, particularly with respect to regressions, of which there were relatively few in the present study. Informal observations suggest that there are a relatively large number of between-line regressions in the present study. This may be due to regressions being delayed for longer, (in comparison to regressions reported in the literature), possibly as a consequence of the passage reading format. Other work to be carried out includes a more detailed description of forward saccade measures into and out of words, such as launch site effects on skipping, as well as a more detailed examination of saccade landing distributions and the interplay of effects of *word*  $n$  and  $n + 1$ .

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## Appendix A: R scripts

### Appendix A: Sample R Scripts

#### File Read and Exclusions

```
rm(list = ls())
ls()

#1. Read and Compile Files
#2. Merge Blocks
#3. Exclusions

####1. Read Files
Ed<- rbind(read.delim ("~/Documents/RFiles/SUB02B1C_T.txt", dec = ".", sep="\t",
header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB02B2C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB02B3C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),read.delim ("~/Documents/RFiles/SUB03B1C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB03B2C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB03B3C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),read.delim ("~/Documents/RFiles/SUB05B1C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB05B2C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB05B3C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),read.delim ("~/Documents/RFiles/SUB06B1C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB06B2C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB06B3C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),read.delim ("~/Documents/RFiles/SUB07B1C_T.txt", dec = ".",
sep="\t", header=TRUE,
                    blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\"",
comment.char=""),
            read.delim ("~/Documents/RFiles/SUB07B2C_T.txt", dec = ".",
```

[illegible]

[illegible]

[illegible]

[illegible]

```

dim (Ed); str(Ed); tail(Ed)

l1<-(as.factor(Ed$Token=="[[END]]"))
l2<-which(l1==TRUE)
Ed1<-Ed[-l2,];tail(Ed1)
Ed<-Ed1

Bl      <- rbind(
  read.delim ("~/Documents/RFiles/FCfreq1.txt", dec = ".", sep="\t",
header=TRUE,
  blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\""),
  read.delim ("~/Documents/RFiles/FCfreq2.txt", dec = ".", sep="\t",
header=TRUE,
  blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\""),
  read.delim ("~/Documents/RFiles/FCfreq3.txt", dec = ".", sep="\t",
header=TRUE,
  blank.lines.skip = TRUE, as.is=TRUE, fill = TRUE, quote="\""),
comment.char="")
dim (Bl); str(Bl); tail(Bl)

#3.Creating new variables

## deconstructing sub name info
Ed$sub      <- substr(Ed$SName,4,5)
Ed$block    <- substr(Ed$SName,7,7)
head(cbind(Ed$SName, Ed$sub, Ed$block))
head(cbind(Ed$SName, Ed$sub, Ed$block, Ed$Token, Ed$P1FxC1),50)

##### adding block info to token ID to make it unique

Ed$TID = 99999
i1<-which(Ed$block=="1")
i2<-which(Ed$block=="2")
i3<-which(Ed$block=="3")

Ed$TID[i1] <- Ed$TokenID[i1]
Ed$TID[i2] <- Ed$TokenID[i2] + 3000
Ed$TID[i3] <- Ed$TokenID[i3] + 6000
max(Ed$TID)

Bl$TID = 99999
j1<-which(Bl$Block=="1")
j2<-which(Bl$Block=="2")
j3<-which(Bl$Block=="3")
Bl$TID[j1] <- Bl$TokenID[j1]
Bl$TID[j2] <- Bl$TokenID[j2] + 3000
Bl$TID[j3] <- Bl$TokenID[j3] + 6000
max(Bl$TID)

#2. Merge data file and tokens file
m1 <- merge(Ed, Bl, by="TID", all=T, incomparables = NA)
dim(m1); str(m1)

### General data checking
xtabs(~sub+Block+Eye,data=m1) #these numbers should be equal to the number of tokens
in each block

```

### ###3. Exclusions

```

###k1 <-which(m1$FC=="na");dim(m1[-k1,]);dim(m1[k1,])
k2 <-which((m1$FC=="na")|(m1$Disagreement=="1"));dim(m1[-k2,]);dim(m1[k2,])
k3 <-which((m1$FC=="na")|(m1$Disagreement==1)|(m1$xStart==54|m1$xEnd==981)); dim(m1[-
k3,]);dim(m1[k3,])

#k4<-
which((m1$FC=="na")|(m1$Disagreement==1)|(m1$xStart==54|m1$xEnd==981)|(m1$P1LnChS1!=0
|m1$P1LnChS2!=0 | m1$P1LnChS3!=0 | m1$P1LnChS4!=0 | m1$P1LnCh1!=0 | m1$P1LnCh2!=0 |
m1$P1LnCh3!=0 | m1$P1LnCh4!=0 | m1$P2LnChS1!=0 | m1$P2LnChS2!=0 | m1$P2LnCh1!=0 |
m1$P2LnCh2!=0 |
m1$P3LnChS1!=0 | m1$P3LnChS2!=0 | m1$P3LnCh1!=0 | m1$P3LnCh2!=0 )|)
dim(m1[-k4,]);dim(m1[k4,])

#k5<-
which((m1$FC=="na")|(m1$Disagreement==1)|(m1$xStart==54|m1$xEnd==981)|(m1$P1LnChS1==0
|m1$P1LnChS2!=0 | m1$P1LnChS3!=0 | m1$P1LnChS4!=0 | m1$P1LnCh1!=0 | m1$P1LnCh2!=0 |
m1$P1LnCh3!=0 | m1$P1LnCh4!=0 | m1$P2LnChS1!=0 | m1$P2LnChS2!=0 | m1$P2LnCh1!=0 |
m1$P2LnCh2!=0 |
m1$P3LnChS1!=0 | m1$P3LnChS2!=0 | m1$P3LnCh1!=0 | m1$P3LnCh2!=0
)|m1$TokenLen>4);dim(m1[-k5,]);dim(m1[k5,])

#k6<-
which((m1$FC=="na")|(m1$Disagreement==1)|(m1$xStart==54|m1$xEnd==981)|(m1$P1LnChS1!=0
|m1$P1LnChS2!=0 | m1$P1LnChS3!=0 | m1$P1LnChS4!=0 | m1$P1LnCh1!=0 | m1$P1LnCh2!=0 |
m1$P1LnCh3!=0 | m1$P1LnCh4!=0 | m1$P2LnChS1!=0 | m1$P2LnChS2!=0 | m1$P2LnCh1!=0 |
m1$P2LnCh2!=0 |
m1$P3LnChS1!=0 | m1$P3LnChS2!=0 | m1$P3LnCh1!=0 | m1$P3LnCh2!=0
)|m1$TokenLen>4|(m1$P1Fxm1>0 & m1$P1Fxm1<50) | (m1$P1Fxm1>1000)|(m1$P1Fxm2>0 &
m1$P1Fxm2<50) | (m1$P1Fxm2>1000)|(m1$P1Fxm3>0 & m1$P1Fxm3<50) |
(m1$P1Fxm3>1000)|(m1$P1Fxm4>0 & m1$P1Fxm4<50) | (m1$P1Fxm4>1000)|(m1$P2Fxm1>0 &
m1$P2Fxm1<50) | (m1$P2Fxm1>1000)|(m1$P2Fxm2>0 & m1$P2Fxm2<50) |
(m1$P2Fxm2>1000)|(m1$P3Fxm1>0 & m1$P3Fxm1<50) | (m1$P3Fxm1>1000)) ;dim(m1[-
k6,]);dim(m1[k6,])

#k7<-
which((m1$FC=="na")|(m1$Disagreement==1)|(m1$xStart==54|m1$xEnd==981)|(m1$P1LnChS1!=0
|m1$P1LnChS2!=0 | m1$P1LnChS3!=0 | m1$P1LnChS4!=0 | m1$P1LnCh1!=0 | m1$P1LnCh2!=0 |
m1$P1LnCh3!=0 | m1$P1LnCh4!=0 | m1$P2LnChS1!=0 | m1$P2LnChS2!=0 | m1$P2LnCh1!=0 |
m1$P2LnCh2!=0 |m1$P3LnChS1!=0 | m1$P3LnChS2!=0 | m1$P3LnCh1!=0 | m1$P3LnCh2!=0
)|m1$TokenLen>4|(m1$P1Fxm1>0 & m1$P1Fxm1<50) | (m1$P1Fxm1>1000)|(m1$P1Fxm2>0 &
m1$P1Fxm2<50) | (m1$P1Fxm2>1000)|(m1$P1Fxm3>0 & m1$P1Fxm3<50) |
(m1$P1Fxm3>1000)|(m1$P1Fxm4>0 & m1$P1Fxm4<50) | (m1$P1Fxm4>1000)|(m1$P2Fxm1>0 &
m1$P2Fxm1<50) | (m1$P2Fxm1>1000)|(m1$P2Fxm2>0 & m1$P2Fxm2<50) |
(m1$P2Fxm2>1000)|(m1$P3Fxm1>0 & m1$P3Fxm1<50) | (m1$P3Fxm1>1000)|m1$xStart<54)
;dim(m1[-k7,]);dim(m1[k7,])

k8<-which(m1$P1Blink==1 |m1$P2Blink==1 |m1$P3Blink==1
|(m1$FC=="na")|(m1$Disagreement==1)|(m1$xStart==54|m1$xEnd==981)|(m1$P1LnChS1!=0 |
m1$P1LnChS2!=0 | m1$P1LnChS3!=0 | m1$P1LnChS4!=0 | m1$P1LnCh1!=0 | m1$P1LnCh2!=0 |
m1$P1LnCh3!=0 | m1$P1LnCh4!=0 | m1$P2LnChS1!=0 | m1$P2LnChS2!=0 | m1$P2LnCh1!=0 |
m1$P2LnCh2!=0 |m1$P3LnChS1!=0 | m1$P3LnChS2!=0 | m1$P3LnCh1!=0 | m1$P3LnCh2!=0
)|m1$TokenLen>4|(m1$P1Fxm1>0 & m1$P1Fxm1<50) | (m1$P1Fxm1>1000)|(m1$P1Fxm2>0 &
m1$P1Fxm2<50) | (m1$P1Fxm2>1000)|(m1$P1Fxm3>0 & m1$P1Fxm3<50) |
(m1$P1Fxm3>1000)|(m1$P1Fxm4>0 & m1$P1Fxm4<50) | (m1$P1Fxm4>1000)|(m1$P2Fxm1>0 &
m1$P2Fxm1<50) | (m1$P2Fxm1>1000)|(m1$P2Fxm2>0 & m1$P2Fxm2<50) |
(m1$P2Fxm2>1000)|(m1$P3Fxm1>0 & m1$P3Fxm1<50) | (m1$P3Fxm1>1000)|m1$xStart<54)
;dim(m1[-k8,]);dim(m1[k8,])

### just fx tm excl k6<-which((m1$P1Fxm1>0 & m1$P1Fxm1<50) |
(m1$P1Fxm1>1000)|(m1$P1Fxm2>0 & m1$P1Fxm2<50) | (m1$P1Fxm2>1000)|(m1$P1Fxm3>0 &

```



```

m1$P1Fxm3<50) | (m1$P1Fxm3>1000)|(m1$P1Fxm4>0 & m1$P1Fxm4<50) |
(m1$P1Fxm4>1000)|(m1$P2Fxm1>0 & m1$P2Fxm1<50) | (m1$P2Fxm1>1000)|(m1$P2Fxm2>0 &
m1$P2Fxm2<50) | (m1$P2Fxm2>1000)|(m1$P3Fxm1>0 & m1$P3Fxm1<50) | (m1$P3Fxm1>1000))
;dim(m1[-k6,]);dim(m1[k6,])
[1] 449420 129
[1] 2500 129

###[1] 451920 129
> dim(m1[-k1,])
[1] 385920 129
> dim(m1[-k2,])
[1] 362340 129
> dim(m1[-k3,])
[1] 337200 129
> dim(m1[-k4,])
[1] 304900 129
dim(m1[-k5,])
[1] 304649 129
dim(m1[k6,])
[1] 449420 129

### Create new file minus exclusions: m2
m2<-m1[-k8,];dim(m2)
head(m2)

### Right Eye Only
k9<-which(m2$Eye=="L")
dim(m2[k9,]);dim(m2[-k9,])
m3<-m2[-k9,]
dim(m3)

## Data checks
xtabs(~sub+Block+Eye,data=m3)
xtabs(~sub+Block+Skip,data=m3)
xtabs(~sub+Block+P1Skip,data=m3)
xtabs(~FC+Skip,data=m3)
xtabs(~sub+block+TokenLen+ RegrTgt, data=m3)

### Create new variable for landing position - whole character
m3$P1land <- m3$P1Fxl1
ln1<-which(m3$Block==1)
ln2<-which(m3$Block==2|m3$Block==3)

m3$P1land[ln1] <- round(((m3$P1Fxl1[ln1])/2.014)+0.01)
m3$P1land[ln2] <- round(((m3$P1Fxl1[ln2])/1.944)+0.01)

## table(m3$P1land, m3$TokenLen)
      1      2      3      4
1 13846 22536 2025   340
2      0 10339 1908   342
3      0      0    29    65

### To create variable for five levels of frequency
m3$fq<-99999
m3$Freq<-as.numeric(m3$Freq)
f1<-which(m3$Freq>=-1.56019 & m3$Freq<=3.1173)
f2<-which(m3$Freq>3.1173&m3$Freq<=4.94035)
f3<-which(m3$Freq>4.94035&m3$Freq<=6.38341)
f4<-which(m3$Freq>6.38341&m3$Freq<=8.05288)
f5<-which(m3$Freq>8.05288)

```

```

f6<-which(is.na(m3$Freq))

m3$fq[f1]<-1
m3$fq[f2]<-2
m3$fq[f3]<-3
m3$fq[f4]<-4
m3$fq[f5]<-5
m3$fq[f6]<-NA
dim(m3[-f6,])
dim(m3[f6,])

m4<-m3[-f6,]
dim(m4)

## Checks
str(m4$Freq)
head(cbind(m4$fq,m4$Freq),50)
tail(cbind(m3$fq,m3$Freq),200)
head(cbind(m3$fq[m3$fq==99999],m3$Freq[m3$fq==99999]),50)
class(m3$Freq)
dim(m3[m3$Freq=="M",])

library(languageR)

fit1=lmer(P1land ~ TokenLen + (1| sub), data=m4)

fit1=lmer(P1FxTm1 ~ TokenLen + (1| sub), data=m3)
summary(fit1)

Linear mixed model fit by REML
Formula: P1FxTm1 ~ TokenLen + (1 | sub)
Data: m3
      AIC      BIC logLik deviance REMLdev
709905 709941 -354949  709903  709897
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)    487.78   22.086
Residual                    7328.29  85.605
Number of obs: 60470, groups: sub, 30

Fixed effects:
              Estimate Std. Error t value
(Intercept) 223.2120     4.1751   53.46
TokenLen      2.1485     0.5667    3.79

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.250
pvals.fnc(fit1)

fit2=lmer(P1FxTm1 ~ TokenLen*fq + (1| sub), data=m3)
fit2=lmer(P1FxTm1 ~ TokenLen*fq + (1| sub) + (1|TrialInd), data=m3)
anova(fit1,fit2)

fit3=lmer(P1FxTm1 ~ FC*TokenLen + (1| sub), data=m3)
summary(fit3)
Linear mixed model fit by REML
Formula: P1FxTm1 ~ FC * TokenLen + (1 | sub)
Data: m3
      AIC      BIC logLik deviance REMLdev
709901 709955 -354945  709899  709889
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)    488.17   22.095

```

```

Residual          7328.11  85.604
Number of obs: 60470, groups: sub, 30

Fixed effects:
              Estimate Std. Error t value
(Intercept)  223.2689    4.3026   51.89
FCf           2.3926    2.5788    0.93
TokenLen      2.2184    0.7233    3.07
FCf:TokenLen -2.4442    1.6847   -1.45

Correlation of Fixed Effects:
              (Intr) FCf   ToknLn
FCf          -0.205
TokenLen     -0.338  0.563
FCf:TokenLen  0.145 -0.932 -0.429

fit4=lmer(P1Skip ~ FC*TokenLen + (1| sub), data=m3)
summary(fit4)
Linear mixed model fit by REML
Formula: P1Skip ~ FC * TokenLen + (1 | sub)
Data: m3
      AIC      BIC logLik deviance REMLdev
189911 189970 -94949   189864  189899
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)  0.016332  0.12780
Residual                   0.204975  0.45274
Number of obs: 151386, groups: sub, 30

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.958518    0.023829   40.23
FCf           0.001454    0.008058    0.18
TokenLen     -0.222369    0.002529  -87.93
FCf:TokenLen  0.012338    0.005723    2.16

Correlation of Fixed Effects:
              (Intr) FCf   ToknLn
FCf          -0.125
TokenLen     -0.197  0.581
FCf:TokenLen  0.087 -0.933 -0.442
> fit5=lmer(RegrTgt ~ FC*TokenLen + (1| sub), data=m3)
Warning message:
In model.matrix.default(mt, mf, contrasts) :
  variable 'FC' converted to a factor
> fit5
Linear mixed model fit by REML
Formula: RegrTgt ~ FC * TokenLen + (1 | sub)
Data: m3
      AIC      BIC logLik deviance REMLdev
62638 62698 -31313   62587  62626
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)  0.0018541  0.043059
Residual                   0.0884470  0.297400
Number of obs: 151386, groups: sub, 30

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.055038    0.008492    6.481
FCf          -0.050994    0.005293   -9.634
TokenLen      0.028512    0.001661   17.163
FCf:TokenLen  0.042121    0.003759   11.205

Correlation of Fixed Effects:

```

```

      (Intr) FCf    ToknLn
FCf      -0.230
TokenLen -0.362  0.581
FCf:TokenLen 0.160 -0.933 -0.442

fit6=lmer(P1Gaze ~ FC*TokenLen + (1| sub), data=m3)
fit6
Linear mixed model fit by REML
Formula: P1Gaze ~ FC * TokenLen + (1 | sub)
Data: m3
      AIC      BIC logLik deviance REMLdev
1925242 1925302 -962615 1925242 1925230
Random effects:
Groups   Name              Variance Std.Dev.
sub      (Intercept)      2486.5    49.865
Residual                    19502.6   139.652
Number of obs: 151386, groups: sub, 30

Fixed effects:
              Estimate Std. Error t value
(Intercept) -18.3791     9.2056   -2.00
FCf           17.7413     2.4856    7.14
TokenLen      74.0333     0.7801   94.90
FCf:TokenLen -14.5332     1.7652   -8.23

Correlation of Fixed Effects:
      (Intr) FCf    ToknLn
FCf      -0.100
TokenLen -0.157  0.581
FCf:TokenLen 0.069 -0.933 -0.442

t=... p

```

## Basic Data Commands

```

### Checking general descriptives - general picture of data
}
tapply(df$P1Skip, df$TokenLen, mean)

tapply(df$TokenLen, df$Eye, mean)

tapply(df$P1Skip, df$Eye, mean)
tapply(df$Skip, df$Eye, mean)
tapply(df$P1FxFNum, df$TokenLen, mean)

tapply(df$P1FxFNum, df$Eye, mean)
tapply(df$P1FxFm1, df$Eye, mean)
tapply(df$P1FxFm1, df$TokenLen, mean)
tapply(df$P1FxFm1, df$Freq, mean)
tapply(df$TokRdTm, df$TokenLen, mean)
tapply(df$P1Gaze, df$TokenLen, mean)
tapply(df$P1ScOut1, df$TokenLen, mean)
tapply(m3$P1land, m3$TokenLen, mean)

#New variables for first and single fixation duration:

class(m4$fq)
class(m4$FC)
class(m4$TokenLen)

```

```
###Tables of descriptives
```

```
table(m4$fq)
  1    2    3    4    5
24984 24167 26639 27433 23420
```

```
table(m4$fq,m4$TokenLen)
  1    2    3    4
1 1330 20481 2607 566
2 4656 19062 449   0
3 7731 18707 201   0
4 22241 5192   0   0
5 23420   0   0   0
```

```
tapply(m3$P1Fxm1, m3$fq, mean, na.rm=T)
tapply(m3$P1Skip,m3$fq, mean)
tapply(m3$RegrTgt,m3$fq, mean, na.rm=T)
tapply(m3$P1Gaze,m3$fq, mean,na.rm=T)
tapply(m3$TokRdTm,m3$fq, mean,na.rm=T)
```

```
# To include only fixated tokens in Gaze and Total durations
```

```
w1<-m3$P1Gaze>0
w2<-m3$TokRdTm>0
```

```
## Skip - Freq - Wordlength
```

```
skip.len.freq = with(m3, tapply(P1Skip, list(TokenLen,fq), mean, na.rm=T))
barplot(skip.len.freq, beside=T, main = "Skipping rate for words of different length
and frequency", xlab = "Word length (characters) - Frequency", ylab = "Skipping
rate",xlim=c(0,25),ylim=c(0,1))
```

```
fxtm.len.freq = with(m3, tapply(P1Fxm1[-s1], list(TokenLen[-s1],fq[-s1]), mean,
na.rm=T))
barplot(fxtm.len.freq, beside=T, main = "First fixation duration for words of
different length and frequency", xlab = "Word length (characters) - Frequency", ylab =
"First fixation duration (ms)",xlim=c(0,25),ylim=c(0,250))
```

```
sgfx.len.freq = with(m3, tapply(P1Fxm1[s1], list(TokenLen[s1],fq[s1]), mean,
na.rm=T))
barplot(sgfx.len.freq, beside=T, main = "Single fixation duration for words of
different length and frequency", xlab = "Word length (characters) - Frequency", ylab =
"Single fixation duration (ms)",xlim=c(0,25),ylim=c(0,250))
```

```
gz.len.freq = with(m3, tapply(P1Gaze[w1], list(TokenLen[w1],fq[w1]), mean, na.rm=T))
barplot(gz.len.freq, beside=T, main = "First pass gaze duration for words of different
length and frequency", xlab = "Word length (characters) - Frequency", ylab = "First
pass gaze duration (ms)",xlim=c(0,25),ylim=c(0,400))
```

```
tkrd.len.freq = with(m3, tapply(TokRdTm[w2], list(TokenLen[w2],fq[w2]), mean,
na.rm=T))
barplot(tkrd.len.freq, beside=T, main = "Total reading time for words of different
length and frequency", xlab = "Word length (characters) - Frequency", ylab = "Total
reading time (ms)",xlim=c(0,25),ylim=c(0,400))
```

```
reg.len.freq = with(m3, tapply(RegrTgt, list(TokenLen,fq), mean, na.rm=T))
barplot(reg.len.freq, beside=T, main = "Regression rate for words of different length
and frequency", xlab = "Word length (characters) - Frequency", ylab = "Regression
rate",xlim=c(0,40),ylim=c(0,0.2))
```

```
table(m3$P1Skip[f1])
```

```
table( m3$P1Fxm1)
```

```
GRAPHS
```

```
1.
```

```

tapply(clean3$P1Skip, clean3$TokenLen, mean)
      1      2      3      4      5      7
0.7496940 0.4392148 0.2037037 0.1692308 0.0000000 0.9870130
> cell.means=tapply(clean3$P1Skip, clean3$TokenLen, mean)
> cell.means
      1      2      3      4      5      7
0.7496940 0.4392148 0.2037037 0.1692308 0.0000000 0.9870130
> barplot(cell.means, beside=T, legend=T, ylim=c(0,1))

2.
tapply(clean3$P1Fxm1, clean3$TokenLen, mean, na.rm=T)
      1      2      3      4      5      7
227.5371 234.6301 235.3488 256.5185 258.4000 152.0000
> dur.means=tapply(clean3$P1Fxm1, clean3$TokenLen, mean, na.rm=T)
> barplot(dur.means, beside=T, legend=T, ylim=c(0,1))
> barplot(dur.means, beside=T, legend=T, ylim=c(100,250))

```

## Modeling

```

library(lme4)
library(languageR)

#### First fixation time

fxtm1=lmer(P1Fxm1 ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm1)

fxtm2=lmer(P1Fxm1 ~ fq + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm2)
anova(fxtm1, fxtm2)

fxtm3=lmer(P1Fxm1 ~ TokenLen + fq + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm3)
anova(fxtm2, fxtm3)

fxtm4=lmer(P1Fxm1 ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm4)
anova(fxtm4, fxtm3)

fxtm5=lmer(P1Fxm1 ~ FC + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm5)

fxtm6=lmer(P1Fxm1 ~ TokenLen*fq*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm6)
anova(fxtm6, fxtm4)

fxtm7=lmer(P1Fxm1 ~ TokenLen + fq+FC + (1| sub)+(1|TrialInd), data=m4)
summary(fxtm7)
anova(fxtm6, fxtm7)

pvals.fnc(fxtm7)
pvals.fnc(skip3)
pvals.fnc(gaze4)

$fixed
      Estimate MCMCmean HPD95lower HPD95upper pMCMC Pr(>|t|)
(Intercept) 244.9574 244.9135    234.652    255.2915 0.0001  0.0000
TokenLen    -3.3347  -3.3352     -6.473     -0.4093 0.0344  0.0304
fq          -2.5308  -2.5290     -4.263     -0.7863 0.0064  0.0043

```

```

TokenLen:fq -0.2332 -0.2351 -1.229 0.8475 0.6518 0.6585

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1 sub (Intercept) 20.7256 20.7463 21.0975 15.3287 27.7646
2 TrialInd (Intercept) 2.3910 2.8326 3.1568 1.0528 5.9516
3 Residual      84.5859 84.5906 84.5914 84.0570 85.1119

pvals.fnc(fxtm7)
$fixed
      Estimate MCMCmean HPD95lower HPD95upper pMCMC
(Intercept) 244.519 244.507 235.2019 254.006 0.0001
TokenLen    -3.541 -3.533 -5.3045 -1.719 0.0002
fq          -3.204 -3.207 -4.0597 -2.408 0.0001
FCf         1.726 1.741 -0.4987 3.893 0.1270
      Pr(>|t|)
(Intercept) 0.0000
TokenLen    0.0001
fq          0.0000
FCf         0.1199

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean
1 sub (Intercept) 20.2406 20.4856 20.5616
2 TrialInd (Intercept) 2.3261 2.7209 3.0652
3 Residual      83.9942 83.9981 83.9997
  HPD95lower HPD95upper
1 15.2816 26.0497
2 0.9456 5.8488
3 83.4657 84.5446

##### Skipping
skip1=glmer(P1Skip ~ TokenLen + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip1)

skip2=glmer(P1Skip ~ fq + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip2)
anova(skip1,skip2)

skip3=lmer(P1Skip ~ TokenLen +fq + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip3)
anova(skip3,skip1)
anova(skip3,skip2)

skip4=lmer(P1Skip ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip4)
anova(skip4,skip3)

skip5=lmer(P1Skip ~ FC + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip5)

skip6=lmer(P1Skip ~ FC + TokenLen + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip6)
anova(skip6,skip1)

skip7=lmer(P1Skip ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4, family=binomial)
summary(skip7)
anova(skip7,skip6)

skip8=lmer(P1Skip ~ FC + TokenLen + fq + (1| sub)+(1|TrialInd), data=m4,
family=binomial)
summary(skip8)
anova(skip8,skip3)

```

```

Linear mixed model fit by REML
Formula: P1Skip ~ TokenLen + (1 | sub) + (1 | TrialInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
163046 163095 -81518   163020  163036
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)    0.01566698 0.125168
TrialInd (Intercept)    0.00010488 0.010241
Residual                    0.20292407 0.450471
Number of obs: 131009, groups: sub, 29; TrialInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.979326   0.023843   41.07
TokenLen     -0.227428   0.002188  -103.95

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.144

```

###

```

Linear mixed model fit by REML
Formula: P1Skip ~ fq + (1 | sub) + (1 | TrialInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
167390 167439 -83690   167362  167380
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)    1.5710e-02 0.125341
TrialInd (Intercept)    9.3682e-05 0.009679
Residual                    2.0977e-01 0.458001
Number of obs: 131009, groups: sub, 29; TrialInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.4086000   0.0237523   17.20
fq           0.0715138   0.0009095    78.63

Correlation of Fixed Effects:
      (Intr)
fq -0.115

```

####

```

Linear mixed model fit by REML
Formula: P1Skip ~ FC + (1 | sub) + (1 | TrialInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
170378 170427 -85184   170352  170368
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)    0.01573965 0.125458
TrialInd (Intercept)    0.00013724 0.011715
Residual                    0.21460514 0.463255
Number of obs: 131009, groups: sub, 29; TrialInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.569793   0.023768   23.97
FCf          0.148033   0.002664   55.56

Correlation of Fixed Effects:

```



```

      (Intr)
FCf -0.041

#### ANOVAs
anova(skip1,skip2)
Data: m4
Models:
skip1: P1Skip ~ TokenLen + (1 | sub) + (1 | TrialInd)
skip2: P1Skip ~ fq + (1 | sub) + (1 | TrialInd)
      Df    AIC    BIC logLik Chisq Chi Df Pr(>Chisq)
skip1  5 163030 163079 -81510
skip2  5 167372 167421 -83681      0      0 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

###
anova(skip3,skip1)
Data: m4
Models:
skip1: P1Skip ~ TokenLen + (1 | sub) + (1 | TrialInd)
skip3: P1Skip ~ TokenLen + fq + (1 | sub) + (1 | TrialInd)
      Df    AIC    BIC logLik Chisq Chi Df Pr(>Chisq)
skip1  5 163030 163079 -81510
skip3  6 162916 162975 -81452 115.99      1 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>

##### Gaze
gaze1=lmer(P1Gaze ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(gaze1)

gaze2=lmer(P1Gaze ~ fq + (1| sub)+(1|TrialInd), data=m4)
summary(gaze2)
anova(gaze1,gaze2)

gaze3=lmer(P1Gaze ~ TokenLen + fq + (1| sub)+(1|TrialInd), data=m4)
summary(gaze3)
anova(gaze1,gaze3)

gaze4=lmer(P1Gaze ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(gaze4)
anova(gaze4,gaze3)

gaze5=lmer(P1Gaze ~ FC + (1| sub)+(1|TrialInd), data=m4)
summary(gaze5)

gaze6=lmer(P1Gaze ~ FC + TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(gaze6)
anova(gaze6,gaze1)

gaze7=lmer(P1Gaze ~ TokenLen*fq + FC +(1| sub)+(1|TrialInd), data=m4)
summary(gaze7)
anova(gaze7,gaze4)

gaze8=lmer(P1Gaze ~ TokenLen*fq*FC +(1| sub)+(1|TrialInd), data=m4)
summary(gaze8)
anova(gaze8,gaze4)

fit2=lmer(P1ScIn1 ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit2)

```

```

pvals.fnc(fit2)

fit3=lmer(P1Gaze ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit3)
pvals.fnc(fit3)

fit4=lmer(TokRdTm ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit4)
pvals.fnc(fit4)

fit5=lmer(P1Skip ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit5)
pvals.fnc(fit5)

fit6=lmer(RegrTgt ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit6)
pvals.fnc(fit6)

fit7=lmer(P1Land ~ TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit7)
pvals.fnc(fit7)

fit8=lmer(P1Fxm1 ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit1)
pvals.fnc(fit1)

fit9=lmer(P1ScIn1 ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit2)
pvals.fnc(fit2)

fit10=lmer(P1Gaze ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit3)
pvals.fnc(fit3)

fit11=lmer(TokRdTm ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit4)
pvals.fnc(fit4)

fit12=lmer(P1Skip ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit5)
pvals.fnc(fit5)

fit13=lmer(RegrTgt ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit6)
pvals.fnc(fit6)

fit14=lmer(P1Land ~ TokenLen*FC + (1| sub)+(1|TrialInd), data=m4)
summary(fit6)
pvals.fnc(fit6)

fit15=lmer(P1Fxm1 ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit1)
pvals.fnc(fit1)

fit16=lmer(P1ScIn1 ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit2)
pvals.fnc(fit2)

fit17=lmer(P1Gaze ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit3)
pvals.fnc(fit3)

fit18=lmer(TokRdTm ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit4)
pvals.fnc(fit4)

```

```

fit19=lmer(P1Skip ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit5)
pvals.fnc(fit5)

fit20=lmer(RegrTgt ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit6)
pvals.fnc(fit6)

fit21=lmer(P1Land ~ FC*TokenLen + (1| sub)+(1|TrialInd), data=m4)
summary(fit7)
pvals.fnc(fit7)

fit22=lmer(P1Fxm1 ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit22)
pvals.fnc(fit22)

fit23=lmer(P1ScIn1 ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit23)
pvals.fnc(fit23)

fit24=lmer(P1Gaze ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit24)
pvals.fnc(fit24)

fit25=lmer(TokRdTm ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit25)
pvals.fnc(fit25)

fit26=lmer(P1Skip ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit26)
pvals.fnc(fit26)

fit27=lmer(RegrTgt ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit27)
pvals.fnc(fit27)

fit28=lmer(P1land ~ TokenLen*fq + (1| sub)+(1|TrialInd), data=m4)
summary(fit28)
pvals.fnc(fit28)


fit1=lmer(P1land ~ TokenLen + (1| sub), data=m4)
> summary(fit1)
Linear mixed model fit by REML
Formula: P1land ~ TokenLen + (1| sub)
Data: m4
    AIC   BIC logLik deviance REMLdev
47736 47771 -23864   47709   47728
Random effects:
Groups   Name             Variance Std.Dev.
sub      (Intercept)  0.00048066 0.021924
Residual                    0.15384698 0.392233
Number of obs: 49332, groups: sub, 29

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.761395   0.007013  108.58
TokenLen     0.266121   0.003061   86.95

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.771
> pvals.fnc(fit1)

```

```

$fixed
      Estimate MCMCmean HPD95lower HPD95upper pMCMC Pr(>|t|)
(Intercept)  0.7614   0.7615    0.7479    0.7759 0.0001      0
TokenLen     0.2661   0.2661    0.2600    0.2721 0.0001      0

$random
      Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept)  0.0219    0.0225   0.0229    0.0163    0.0304
2 Residual              0.3922    0.3922   0.3922    0.3898    0.3948

> fit1=lmer(P1FxTm1 ~ TokenLen + (1| sub)(1|Trial), data=m4)
Error in 1 | sub :
  operations are possible only for numeric or logical types
> fit1=lmer(P1land ~ TokenLen + (1| sub)(1|Trial), data=m4)
Error in 1 | sub :
  operations are possible only for numeric or logical types
> fit1=lmer(P1FxTm1 ~ TokenLen + (1| sub)+(1|Trial), data=m4)
Error in eval(expr, envir, enclos) : object 'Trial' not found
> fit1=lmer(P1FxTm1 ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit1)
Linear mixed model fit by REML
Formula: P1FxTm1 ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
578066 578110 -289028  578061  578056
Random effects:
Groups   Name      Variance Std.Dev.
sub      (Intercept) 428.1386 20.69151
ItemInd  (Intercept)  0.4599  0.67816
Residual              7166.7276 84.65653
Number of obs: 49332, groups: sub, 29; ItemInd, 7

Fixed effects:
      Estimate Std. Error t value
(Intercept) 230.5107     4.0455  56.98
TokenLen     0.5921     0.6608   0.90

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.289
> pvals.fnc(fit1)
$fixed
      Estimate MCMCmean HPD95lower HPD95upper pMCMC Pr(>|t|)
(Intercept) 230.5107 230.4848  222.6110  239.212 0.0001  0.0000
TokenLen     0.5921  0.5894  -0.6791    1.875 0.3710  0.3703

$random
      Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept) 20.6915    20.8630  21.1588    16.6661    26.5865
2 ItemInd (Intercept)  0.6782    0.7658   0.9473    0.0000    2.5804
3 Residual              84.6565    84.6586  84.6572    84.1050    85.1672

> fit2=lmer(P1FxTm1[-s1] ~ TokenLen[-s1] + (1| sub)+(1|ItemInd), data=m4)
Error in model.frame.default(data = m4, formula = P1FxTm1[-s1] ~ TokenLen[-s1] + :
  variable lengths differ (found for 'sub')
> fit2=lmer(P1FxTm1[-s1] ~ TokenLen[-s1] + (1| sub[-s1])+(1|ItemInd), data=m4)
Error in model.frame.default(data = m4, formula = P1FxTm1[-s1] ~ TokenLen[-s1] + :
  variable lengths differ (found for 'ItemInd')
> fit2=lmer(P1FxTm1[-s1] ~ TokenLen[-s1] + (1| sub[-s1])+(1|ItemInd[-s1]), data=m4)
Error in sub[-s1] : object of type 'closure' is not subsettable
> fit2=lmer(Sgfx ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
Error in model.frame.default(data = m4, formula = Sgfx ~ TokenLen + (1 + :
  variable lengths differ (found for 'TokenLen')
> fit3=lmer(P1Gaze ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit3)

```

```

Linear mixed model fit by REML
Formula: P1Gaze ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
    AIC      BIC  logLik deviance REMLdev
1655055 1655104 -827522  1655052 1655045
Random effects:
Groups      Name      Variance Std.Dev.
sub      (Intercept)  2096.813  45.791
ItemInd   (Intercept)   11.182   3.344
Residual                17921.538 133.871
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept) -10.0961     8.6673   -1.16
TokenLen      67.3518     0.6502  103.59

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.118
> pvals.fnc(fit3)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)   -10.10     -10.05     -26.73      6.438 0.2254  0.2441
TokenLen        67.35      67.34      66.15     68.721 0.0001  0.0000

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept) 45.7910    43.4995  44.2165    33.5147    55.0963
2 ItemInd (Intercept)  3.3440     3.9868  4.3990     1.3216     8.2547
3 Residual                133.8713   133.8744 133.8754   133.3723   134.4022

> fit2=lmer(P1ScIn1 ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit2)
Linear mixed model fit by REML
Formula: P1ScIn1 ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
    AIC      BIC  logLik deviance REMLdev
237244 237288 -118617  237227 237234
Random effects:
Groups      Name      Variance Std.Dev.
sub      (Intercept)  1.611618  1.26950
ItemInd   (Intercept)  0.012328  0.11103
Residual                7.150593  2.67406
Number of obs: 49332, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)   3.48093     0.24274  14.340
TokenLen      0.16979     0.02089   8.129

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.153
> pvals.fnc(fit2)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)    3.4809    3.4830     3.0411     3.9529 0.0001  0
TokenLen       0.1698    0.1698     0.1302     0.2115 0.0001  0

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept) 1.2695     1.1548  1.1694     0.9043     1.4473
2 ItemInd (Intercept)  0.1110     0.1320  0.1499     0.0432     0.3026
3 Residual                2.6741     2.6742  2.6742     2.6580     2.6907

```

```

> fit3=lmer(P1Gaze ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit3)
Linear mixed model fit by REML
Formula: P1Gaze ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC  logLik deviance REMLdev
1655055 1655104 -827522  1655052 1655045
Random effects:
Groups   Name      Variance Std.Dev.
sub      (Intercept) 2096.813  45.791
ItemInd  (Intercept)  11.182   3.344
Residual                    17921.538 133.871
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept) -10.0961    8.6673   -1.16
TokenLen      67.3518    0.6502  103.59

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.118
> pvals.fnc(fit3)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)   -10.10    -10.15    -26.27      6.593 0.2244  0.2441
TokenLen        67.35     67.35     66.10     68.617 0.0001  0.0000

$random
      Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept) 45.7910   43.2843  43.2714   32.7596   53.5289
2 ItemInd (Intercept)  3.3440    3.8741  4.2641    1.4799    8.0837
3 Residual                    133.8713  133.8733 133.8729   133.3619  134.3875

> fit4=lmer(TokRdTm ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit4)
Linear mixed model fit by REML
Formula: TokRdTm ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC  logLik deviance REMLdev
1726063 1726112 -863027  1726062 1726053
Random effects:
Groups   Name      Variance Std.Dev.
sub      (Intercept) 2960.284  54.4085
ItemInd  (Intercept)  46.018   6.7837
Residual                    30815.866 175.5445
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  -4.8728    10.5232   -0.46
TokenLen      86.3784    0.8526  101.31

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.128
> pvals.fnc(fit4)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)   -4.873    -4.847    -26.00      16.07 0.6524  0.6433
TokenLen       86.378    86.376     84.76     88.04 0.0001  0.0000

$random
      Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper

```

```

1      sub (Intercept)  54.4085    53.8111  53.8046    41.1503    68.3587
2 ItemInd (Intercept)   6.7837     8.0836   8.8745     3.7861    15.9506
3 Residual              175.5445    175.5457 175.5443    174.8504    176.2050

> fit5=lmer(P1Skip ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit5)
Linear mixed model fit by REML
Formula: P1Skip ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
163073 163122 -81532   163047  163063
Random effects:
Groups   Name      Variance Std.Dev.
sub      (Intercept) 0.01566505 0.125160
ItemInd  (Intercept) 0.00011560 0.010752
Residual              0.20296677 0.450518
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.983090    0.023889   41.15
TokenLen     -0.227563    0.002188 -104.00

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.144
> pvals.fnc(fit5)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)   0.9831    0.9837    0.9384    1.0320 0.0001      0
TokenLen      -0.2276   -0.2276   -0.2319   -0.2235 0.0001      0

$random
      Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept)  0.1252    0.1241    0.1238    0.0961    0.1521
2 ItemInd (Intercept)  0.0108    0.0128    0.0141    0.0045    0.0265
3 Residual              0.4505    0.4505    0.4505    0.4487    0.4522

> fit6=lmer(RegrTgt ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
> summary(fit6)
Linear mixed model fit by REML
Formula: RegrTgt ~ TokenLen + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
38540 38589 -19265   38510  38530
Random effects:
Groups   Name      Variance Std.Dev.
sub      (Intercept) 1.1670e-03 0.0341616
ItemInd  (Intercept) 6.9224e-06 0.0026310
Residual              7.8482e-02 0.2801462
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.04309    0.00682   6.318
TokenLen     0.02852    0.00136  20.969

Correlation of Fixed Effects:
      (Intr)
TokenLen -0.313
> pvals.fnc(fit6)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)   0.0431    0.0431    0.0285    0.0569 0.0001      0
TokenLen      0.0285    0.0285    0.0258    0.0312 0.0001      0

```

```

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1    sub (Intercept)  0.0342    0.0351    0.0354    0.0264    0.0459
2 ItemInd (Intercept)  0.0026    0.0031    0.0036    0.0000    0.0084
3 Residual              0.2801    0.2802    0.2802    0.2791    0.2812

>
> fit7=lmer(P1Land ~ TokenLen + (1| sub)+(1|ItemInd), data=m4)
Error in eval(expr, envir, enclos) : object 'P1Land' not found
> summary(fit7)
Error: object 'fit7' not found
Error in summary(fit7) :
  error in evaluating the argument 'object' in selecting a method for function
  'summary'
> pvals.fnc(fit7)
Error in is(object, "mer") : object 'fit7' not found
> fit22=lmer(P1Fxm1 ~ TokenLen*fq + (1| sub)+(1|ItemInd), data=m4)
> summary(fit22)
Linear mixed model fit by REML
Formula: P1Fxm1 ~ TokenLen * fq + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
578013 578074 -288999  578005  577999
Random effects:
 Groups      Name      Variance Std.Dev.
 sub      (Intercept)  429.44820 20.72313
 ItemInd  (Intercept)   0.29501  0.54315
 Residual              7158.90328 84.61030
Number of obs: 49332, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept) 244.3317    5.0182   48.69
TokenLen     -2.9729    1.5396   -1.93
fq           -2.3251    0.8870   -2.62
TokenLen:fq  -0.3491    0.5274   -0.66

Correlation of Fixed Effects:
      (Intr) Tokln fq
TokenLen -0.606
fq        -0.562  0.903
TokenLen:fq 0.430 -0.819 -0.903
> pvals.fnc(fit22)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept) 244.3317  244.383    234.196    254.3405  0.0001  0.0000
TokenLen     -2.9729  -2.966     -6.026     0.0541  0.0590  0.0535
fq           -2.3251  -2.318     -3.973    -0.5225  0.0086  0.0088
TokenLen:fq  -0.3491  -0.353     -1.353     0.7006  0.5062  0.5080

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1    sub (Intercept) 20.7231    20.6289    20.9758    15.6281    26.8745
2 ItemInd (Intercept)  0.5431     0.6793     0.8700     0.0000     2.5644
3 Residual              84.6103    84.6083    84.6104    84.1007    85.1489

>
> fit23=lmer(P1ScIn1 ~ TokenLen*fq + (1| sub)+(1|ItemInd), data=m4)
> summary(fit23)
Linear mixed model fit by REML
Formula: P1ScIn1 ~ TokenLen * fq + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
237187 237249 -118587  237153  237173

```



```

Random effects:
  Groups   Name      Variance Std.Dev.
sub      (Intercept) 1.615083 1.27086
ItemInd  (Intercept) 0.011723 0.10827
Residual              7.140167 2.67211
Number of obs: 49332, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  3.05730    0.26031  11.745
TokenLen     0.25582    0.04866   5.257
fq           0.05680    0.02803   2.026
TokenLen:fq  0.02952    0.01666   1.772

Correlation of Fixed Effects:
              (Intr) ToknLn fq
TokenLen     -0.370
fq           -0.343  0.903
TokenLen:fq  0.262 -0.819 -0.903
> pvals.fnc(fit23)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)  3.0573    3.0545    2.5775    3.5446 0.0001  0.0000
TokenLen     0.2558    0.2560    0.1580    0.3511 0.0001  0.0000
fq           0.0568    0.0569   -0.0009    0.1096 0.0440  0.0428
TokenLen:fq  0.0295    0.0295   -0.0041    0.0614 0.0798  0.0765

$random
  Groups   Name      Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1 sub      (Intercept) 1.2709    1.1576    1.1752    0.9454    1.4696
2 ItemInd  (Intercept) 0.1083    0.1253    0.1374    0.0433    0.2611
3 Residual              2.6721    2.6722    2.6723    2.6559    2.6890

>
> fit24=lmer(P1Gaze ~ TokenLen*fq + (1| sub)+(1|ItemInd), data=m4)
> summary(fit24)
Linear mixed model fit by REML
Formula: P1Gaze ~ TokenLen * fq + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
1654891 1654959 -827438  1654884 1654877
Random effects:
  Groups   Name      Variance Std.Dev.
sub      (Intercept) 2097.243  45.7957
ItemInd  (Intercept)  10.403   3.2254
Residual              17898.921 133.7868
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept) -4.0765    9.2086   -0.44
TokenLen     70.9312    1.7038  41.63
fq           1.8086    0.8897   2.03
TokenLen:fq  -4.0954    0.5714  -7.17

Correlation of Fixed Effects:
              (Intr) ToknLn fq
TokenLen     -0.340
fq           -0.324  0.924
TokenLen:fq  0.252 -0.848 -0.910
> pvals.fnc(fit24)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept) -4.077    -4.071   -22.4789    12.916 0.6500  0.6580
TokenLen     70.931    70.951    67.5722    74.192 0.0001  0.0000

```

```

fq          1.809    1.818    0.0244    3.526 0.0422    0.0421
TokenLen:fq -4.095   -4.104   -5.2304   -2.990 0.0001    0.0000

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept) 45.7957   42.4984  43.4495   34.0191   54.9529
2 ItemInd (Intercept)  3.2254    3.8039  4.2060    1.3185    7.8457
3 Residual              133.7868   133.7849 133.7837   133.2191   134.2658

>
> fit25=lmer(TokRdTm ~ TokenLen*fq + (1| sub)+(1|ItemInd), data=m4)
> summary(fit25)
Linear mixed model fit by REML
Formula: TokRdTm ~ TokenLen * fq + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
1725778 1725846 -862882  1725773 1725764
Random effects:
  Groups      Name      Variance Std.Dev.
  sub      (Intercept) 2960.152  54.407
  ItemInd  (Intercept)   44.182   6.647
  Residual              30748.693 175.353
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  17.3095    11.2802    1.53
TokenLen      86.4109     2.2332   38.69
fq           -0.3536     1.1661   -0.30
TokenLen:fq   -5.0783     0.7489   -6.78

Correlation of Fixed Effects:
              (Intr) TokLn fq
TokenLen     -0.363
fq           -0.346  0.924
TokenLen:fq   0.269 -0.848 -0.910
> pvals.fnc(fit25)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)  17.3095  17.3423    -6.731    40.363 0.1432  0.1249
TokenLen      86.4109  86.4116    82.238    90.853 0.0001  0.0000
fq           -0.3536 -0.3547    -2.709    1.808 0.7582  0.7617
TokenLen:fq   -5.0783 -5.0808    -6.574    -3.634 0.0001  0.0000

$random
  Groups      Name Std.Dev. MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept) 54.4073   54.5042  55.5639   43.1595   70.5824
2 ItemInd (Intercept)  6.6469    7.9870  8.8041    3.5326   16.0366
3 Residual              175.3531   175.3575 175.3534   174.6922   176.0464

>
> fit26=lmer(P1Skip ~ TokenLen*fq + (1| sub)+(1|ItemInd), data=m4)
> summary(fit26)
Linear mixed model fit by REML
Formula: P1Skip ~ TokenLen * fq + (1 | sub) + (1 | ItemInd)
Data: m4
      AIC      BIC logLik deviance REMLdev
162981 163050 -81484  162929 162967
Random effects:
  Groups      Name      Variance Std.Dev.
  sub      (Intercept) 0.01566433 0.125157
  ItemInd  (Intercept) 0.00010981 0.010479
  Residual              0.20278703 0.450319
Number of obs: 131009, groups: sub, 29; ItemInd, 7

```

```

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.9033847  0.0260864   34.63
TokenLen     -0.2027482  0.0057347  -35.35
fq           0.0145669  0.0029946    4.86
TokenLen:fq  -0.0007307  0.0019233   -0.38

Correlation of Fixed Effects:
      (Intr) ToknLn fq
TokenLen  -0.404
fq        -0.384  0.924
TokenLen:fq  0.299 -0.848 -0.910
> pvals.fnc(fit26)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)  0.9034    0.9035    0.8518    0.9554 0.0001  0.000
TokenLen     -0.2027   -0.2028   -0.2141   -0.1919 0.0001  0.000
fq           0.0146    0.0146    0.0090    0.0207 0.0001  0.000
TokenLen:fq  -0.0007   -0.0007   -0.0044    0.0030 0.7110  0.704

$random
      Groups      Name Std.Dev.  MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept)  0.1252    0.1207    0.1219    0.0927    0.1520
2 ItemInd (Intercept)  0.0105    0.0125    0.0140    0.0044    0.0270
3 Residual              0.4503    0.4503    0.4503    0.4487    0.4521

>
> fit27=lmer(RegrTgt ~ TokenLen*fq + (1| sub)+(1|ItemInd), data=m4)
> summary(fit27)
Linear mixed model fit by REML
Formula:   RegrTgt ~ TokenLen * fq + (1 | sub) + (1 | ItemInd)
Data:      m4
      AIC      BIC logLik deviance REMLdev
 38508 38576 -19247   38450   38494
Random effects:
      Groups      Name      Variance  Std.Dev.
      sub      (Intercept) 1.1668e-03 0.0341578
      ItemInd (Intercept) 8.3744e-06 0.0028938
      Residual              7.8447e-02 0.2800834
Number of obs: 131009, groups: sub, 29; ItemInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  0.091641  0.009459   9.688
TokenLen     0.002974  0.003566    0.834
fq          -0.014439  0.001862  -7.754
TokenLen:fq  0.008383  0.001196   7.009

Correlation of Fixed Effects:
      (Intr) ToknLn fq
TokenLen  -0.692
fq        -0.659  0.924
TokenLen:fq  0.513 -0.848 -0.910
> pvals.fnc(fit27)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC Pr(>|t|)
(Intercept)  0.0916    0.0915    0.0725    0.1104 0.0001  0.0000
TokenLen     0.0030    0.0030   -0.0040    0.0099 0.4066  0.4043
fq          -0.0144   -0.0144   -0.0180   -0.0107 0.0001  0.0000
TokenLen:fq  0.0084    0.0084    0.0061    0.0108 0.0001  0.0000

$random
      Groups      Name Std.Dev.  MCMCmedian MCMCmean HPD95lower HPD95upper
1      sub (Intercept)  0.0342    0.0343    0.0350    0.0264    0.0452
2 ItemInd (Intercept)  0.0029    0.0036    0.0040    0.0000    0.0088

```

```

3 Residual                0.2801    0.2801    0.2801    0.2790    0.2812

fxtm7=lmer(P1Fxm1 ~ TokenLen + fq+FC + (1| sub)+(1|TrialInd), data=m4)
Error in inherits(x, "data.frame") : object 'm4' not found
> summary(fxtm7)
Error: object 'fxtm7' not found
Error in summary(fxtm7) :
  error in evaluating the argument 'object' in selecting a method for function
  'summary'
> m4<-m3[-f6,]
> dim(m4)
[1] 126643    149
> fxtm7=lmer(P1Fxm1 ~ TokenLen + fq+FC + (1| sub)+(1|TrialInd), data=m4)
Warning message:
In model.matrix.default(mt, mf, contrasts) :
  variable 'FC' converted to a factor
> summary(fxtm7)
Linear mixed model fit by REML
Formula: P1Fxm1 ~ TokenLen + fq + FC + (1 | sub) + (1 | TrialInd)
Data: m4
      AIC      BIC  logLik deviance REMLdev
539282 539343 -269634   539276   539268
Random effects:
      Groups      Name      Variance Std.Dev.
sub      (Intercept)  409.6808  20.2406
TrialInd (Intercept)    5.4107   2.3261
Residual                    7055.0263  83.9942
Number of obs: 46083, groups: sub, 28; TrialInd, 7

Fixed effects:
              Estimate Std. Error t value
(Intercept)  244.5186    4.6262   52.86
TokenLen     -3.5407    0.9227   -3.84
fq           -3.2045    0.4251   -7.54
FCf           1.7259    1.1098    1.56

Correlation of Fixed Effects:
              (Intr) ToknLn fq
TokenLen  -0.492
fq         -0.402  0.527
FCf        -0.037  0.188 -0.389
> pvals.fnc(fxtm7)
$fixed
              Estimate MCMCmean HPD95lower HPD95upper  pMCMC
(Intercept)  244.519  244.507   235.2019   254.006  0.0001
TokenLen     -3.541  -3.533   -5.3045   -1.719  0.0002
fq           -3.204  -3.207   -4.0597   -2.408  0.0001
FCf           1.726   1.741   -0.4987    3.893  0.1270
              Pr(>|t|)
(Intercept)  0.0000
TokenLen     0.0001
fq           0.0000
FCf          0.1199

$random
      Groups      Name Std.Dev. MCMCmedian MCMCmean
1      sub (Intercept)  20.2406   20.4856  20.5616
2 TrialInd (Intercept)   2.3261    2.7209   3.0652
3 Residual              83.9942   83.9981  83.9997
      HPD95lower HPD95upp

```